# A Bi-level Optimization-based Community Energy Management System for Optimal Energy Sharing and Trading Among Peers

Edstan Fernandez[1], Jahangir Hossain[2], Khizir Mahmud[3], M.S.H. Nizami[1], Muhammad Kashif[1]

[1] *School of Engineering, Macquarie University, North Ryde, Sydney, Australia*
[2] *School of Electrical and Data Engineering, University of Technology Sydney, Sydney, Australia*
[3] *School of Electrical Engineering and Telecommunications, University of New South Wales, Sydney, Australia*

**Abstract**

The economic and environmental benefits of renewable energy have increased in significance over the past decade. Local energy markets can play a vital role in energy transition by facilitating the rapid proliferation of renewable-based energy resources, thereby increasing the renewable energy hosting capacity of the power grid. This paper proposes an energy management system for a smart locality that facilitates local energy trading involving consumers with renewable energy units, a central storage facility, and a power grid. Two optimization frameworks for sharing surplus onsite produced energy are developed here. The first framework maximizes the combined revenue of sellers and buyers, while the second, a game theoretical model, maximizes consumer utilization at the lower level and the revenue of the common storage facility at the higher level. An intensive study is carried out to investigate the benefits of energy sharing that maximizes overall revenue. The results indicate that the grid pricing scheme is a major factor that determines the revenue sharing between the central storage facility entity and the consumers. The first framework results in optimal resource allocation, while the second framework concentrates only on revenue generation. Results indicate that the energy seller profits are higher if the real-time grid prices are used and if the consumers are not charged according to their willingness to pay.

*Keywords:* Peer to peer energy trading, Demand side management, community energy management, willingness to pay, game theory.

**Acronyms**

**CEMS** Community Energy Management System.

**CSF** Central Storage Facility.

**DER** Distributed Energy Resource.

**DSM** Demand Side Management.

**LEM** Local Energy Markets.

**MCP** Market Clearing Price.

**NPV** Net Present Value.

**P2P** Peer to Peer.

**PHEV** Plug-in Hybrid Electric Vehicle.

**PV** Photo Voltaic.

**RES** Renewable Energy Source.

**RTP** Real-time Price.

**WTP** Willingness to Pay.

## 1. Introduction

Climate change is one of the greatest challenges facing modern civilization. A significant portion of greenhouse gases are emitted when fossil fuels are used for electricity generation. Hence, the energy sector is at the center of research activities aimed at analysing the socio-economic incentives supporting the use of renewable energy sources (RESs). This involves integrating multiple challenges to achieve sustainable energy systems not only from an energy consumption and emission reduction perspective but also from the socio-economic impacts it can have.

Consumers with on-site renewable-based distributed energy resources (DERs) can actively engage in the local energy balance by acting as a small-scale producer of energy, and hence they are often referred to as 'Prosumers'. A group of consumers and prosumers can form an intelligent energy community, which is a coherent and intersectoral approach that searches for the best strategy to adopt ~~to satisfy~~ consumer energy requirements [1]. The introduction of local energy markets (LEMs), has enabled prosumers to trade their excess generation or consumption-reduction flexibility locally. A peer- to-peer (P2P) transaction between consumers is a bilateral contract between an energy surplus consumer and an energy deficit consumer to exchange a specific amount of energy at any particular time at an agreed cost [2]. The success of P2P trading lies in its easy implementation, optimal energy sharing and revenue generation. A validation of the potential consumer motives to participate in Demand Side Management (DSM) carried out in [3] surveyed 745 participants. The results suggested that economic incentives, trust in peers, lifestyle and emission reductions are the most important drivers. In Australia, testing is underway to allow consumers to share and trade onsite produced RES power with peers based on blockchain technology.

Numerous research efforts have led to the development of an effective energy management and resource allocation framework for local communities for energy trading among peers. For example, the authors in [4] propose a hybrid energy trading scheme for local P2P energy trading for coordinated end user cost reduction. A P2P platform based on multi-class energy management, which allows energy to be considered as a diverse commodity, to coordinate trading between prosumers with heterogeneous preferences is proposed in [5]. The authors in [6] propose an energy trading game without any central entity, thereby reducing the data sharing and making the system unbiased. A consortium blockchain-based secure P2P energy trading model, for trading surplus electricity among plug-in hybrid electric vehicles (PHEVs) in smart grids is discussed in [7].

The energy exchange in a rural community based on transactive energy trading discussed in [8], allows communities to share power within themselves and with the grid. The model has a cost saving of 0.19% compared to a scenario in which energy exchange was only between the community and the grid. The authors in [9, 10] proposed a common portal called locality electricity trading system (LETS) that manages energy trading. The LETS fixes a price for every transaction based on the customer price and the day ahead trading schedule provided by the participants, thus facilitating a trading agreement. In [11] an energy-sharing model with a price-based demand response is proposed based on the supply demand ratio. The study shows that revenue generation from trading energy between peers is much higher compared to trading energy with the grid at the feed-in tariff. The revenues generated using hour-ahead optimization are found to be lower than the day-ahead optimization due to uncertainties in solar power production. The economic viability of P2P trading using three existing models is evaluated in [12] using various pricing schemes such as flat rate pricing and real-time price (RTP). A P2P energy trading platform 'Elecbay', based on game theory was developed in [13]. The case studies concluded that when energy is traded between consumers, a balance can be attained between local demand and generation, thereby reducing the feed-in to the grid. If there are heterogeneous sets of prosumers and consumers, the microgrid can enhance its revenues using P2P trading. The agent-based approach in [14] ensures the fair distribution of surpluses among agents. The resource distribution is modelled as a coalitional game and the contribution of agents is computed using the Shapley value. A bi-level market with an aggregator and multiple microgrids is modelled in [15]. The model schedules the consumer demand and increases the profits of the microgrids. Many studies model the interaction between various entities such as the consumer, prosumer, central agent and the grid as games [16–18].

The internet of things (IoT) is quickly gaining prominence as a communication link and data processing framework. One such study [19], proposed multi design layers; "core cloud" and "edge clouds" for energy management. Although the results show that there was a 14.28% drop in operation costs due to load shifting, the work does not consider the effect of energy trading between peers.

In this paper, consumers share and trade the surplus energy of RES's among themselves, thus reducing grid dependency. The various entities of the model are focused on maximizing their revenues. Consumers are motivated to take part in LEM strategies if they can gain financial benefits. Having said that, there are many other factors that may also motivate the consumer, such as reductions in greenhouse emissions, preferred comfort levels or preferred sources of energy. In [20], the authors show that consumers are willing to pay for comfort and the potential valuation of environmental benefits. A consumer may have multiple preferences for which they are willing to pay, and hence their utility function may be non-linear. In this paper it is considered that the consumers / prosumers are willing to pay for:

*(i)* energy procurement from the entity who owns the Central Storage Facility (CSF)

*(ii)* energy procurement from neighbors who sell their surplus energy and

*(iii)* consumer comfort.

To this end, a Community Energy Management System (CEMS) is presented in this paper to facilitate local P2P trading among consumers in the community with DER units, a CSF owned by the community, and the power grid. The main innovative contribution of this paper is to formulate the interaction problem for local energy sharing as a Stackelberg game based on bi-level optimization to maximize the utility of all involved parties. The specific contributions of this paper are to:

- Design and implement a CEMS framework for coordinated resource allocation and P2P energy trading,
- Develop a bi-level optimization-based energy sharing model, which in the upper level

maximizes CSF revenues and in the lower level maximizes the consumer utility function,

- Propose a utility function for the P2P trading of the consumers that reflects their preferences, conveniences and willingness to pay,
- Develop a RES pricing scheme for the CSF and evaluate the impact of different pricing schemes set by the utility and the CSF on the overall revenues.

The rest of the paper is organized as follows. Section 2 discusses the system and Section 3 formulates the methodology including the scheduling model and the pricing models. The optimization models used to achieve revenues for the participating entities and their comparison are discussed in Section 4. Section 5 presents the simulation settings, and the results are analysed in Section 6. The paper is concluded in Section 7, which discusses the conclusion, limitations and future work.

## 2. Overview of the Proposed CEMS Framework

The proposed framework of the CEMS is discussed in this section. Fig. 1 illustrates the system overview of the proposed framework for the CEMS. The community consists of multiple consumers, represented by the set $\mathbb{U}$. To have uniform power consumption all through the day, some consumers in the vicinity are considered to be small businesses who have a peak load mid-day, while the residential consumers have their peak load in the late afternoon. Every consumer, $u \in \mathbb{U}$, is considered to have a set of loads consuming power, $P$. These loads consist of base loads $n$ and shiftable loads $m$. The appliances that are powered all through the day, such as the refrigerator and medical equipment are considered as base loads.

The community is interconnected via a bidirectional power and communication link and each consumer is individually connected to the utility grid. Consumer information such as their demand, generation and energy traded are recorded by a smart meter, and the information is transmitted via the communication link to the local controller. The controller manages the scheduling of the various appliances on the premises. Since the quantity of power traded is less, the power losses are negligible, and the communication link failures and latency issues are minimum. We believe the communication protocols and methods discussed in [21] could be easily adopted for the proposed community energy management system.

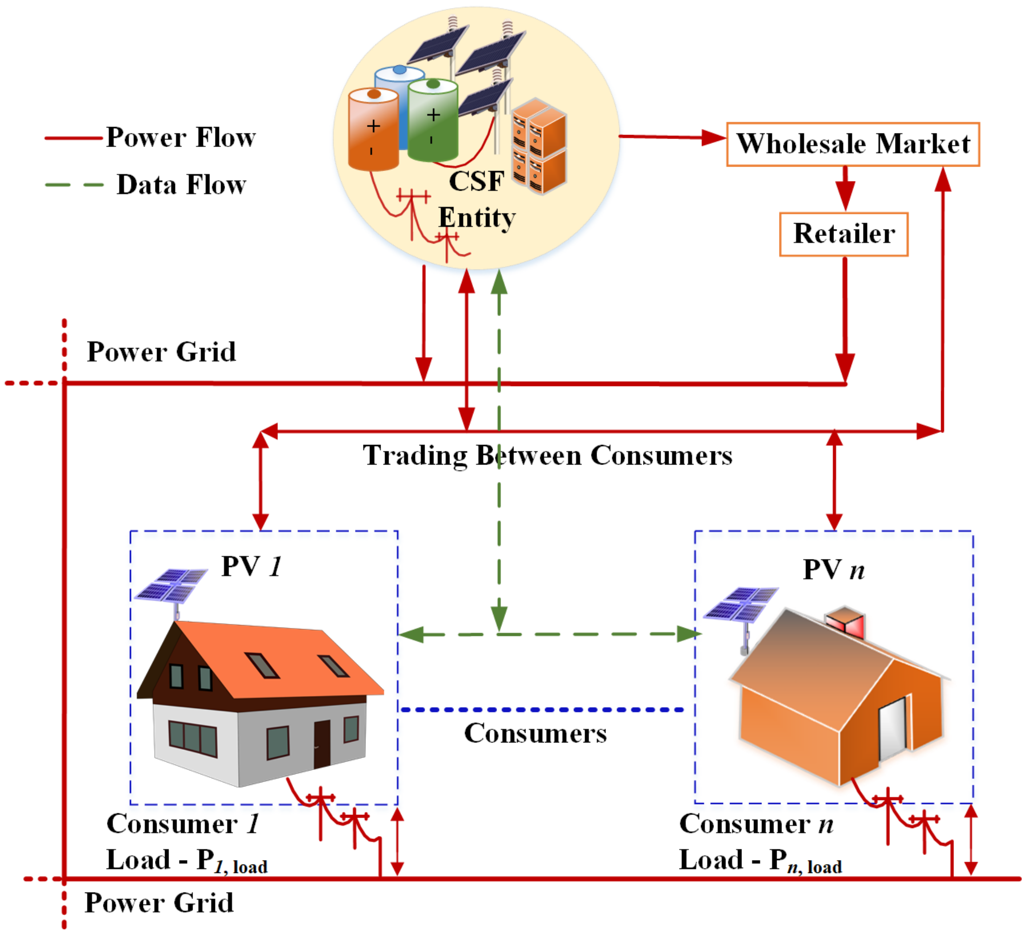



**Figure 1:** Overview of the proposed CEMS framework

The consumption patterns of shiftable loads such as the dishwasher and electric vehicle can be shifted by the controller for efficient scheduling. The consumers have roof top solar panels installed on-site, but none have batteries installed. Consumers use their locally generated photo voltaic (PV) power for meeting their own demand first, and the surplus is traded with neighbors, a CSF, or with the grid. The quantum of power traded between different players in the game is a function of the grid price, the actual demand and the buyers' willingness to pay for RES power procured from various sources.

A separate entity maintains the CSF. For the purpose of this study, it is assumed that the CSF can be charged only by the PV panels installed by the entity or the surplus power produced by the RES of consumers and not from the grid. The power from the PV maintained by the entity is used to charge the CSF. The power from the CSF can be purchased by the consumers or sold to the grid at the market clearing price (MCP). Selling RES generated surplus power to the grid by the consumers is always the last option due to the low feed-in tariff. The feed-in tariff benchmark range for the 2019/20 financial year in Sydney is 8.5 to 10.4 cents per kWh [22]. This may not be profitable to sellers, if the demand is high.

## 3. Methodology

The objective of consumers will be to reduce their utility bill by consuming power that costs them the least. The cost of power procured from the grid is considered the costliest option. Initially, a Mixed-Integer Linear Programming (MILP) day-ahead scheduling model is developed as in [23] that optimizes energy consumption, thereby reducing energy costs without a compromise in user comfort. The schedules of the shiftable loads are zero outside the preferred time of operation set by the consumer. The model provides prosumers with an energy consumption profile for the shiftable appliances. These schedules are used as a reference by the CSF entity and by the peers when prices are set for the energy being traded.

Apart from the day-ahead optimization model, two other optimization models are proposed in this paper. The initial model includes the consumers' utility and the CSF entity revenues, and it maximizes local RES generation. The prosumers are characterized by their utility function, which reflects their preferences. The optimization framework maximizes aggregated consumer utility considering the surplus power generated by the consumers and the CSF. Any surplus power after trading is sold to the grid at the MCP, $P_{MCP}$. The choice of the pricing scheme dictates the revenue sharing between the CSF and the prosumers.

The second optimization is a bi-level model where the CSF owner is aware of the consumers preferences, energy consumption schedule and onsite power generation. In the proposed Stackelberg game all agents in the local energy market have prior knowledge of their RES production and demand at any half hour time slot. The CSF owner is the leader of the Stackelberg game [24], and the consumers are the followers. Upon implementing the Stackelberg game, the CSF entity tries to maximize revenues, while the prosumers maximize their utility function. This is a better revenue model for the CSF entity, but it also results in sub-optimal resource allocation.

### *3.1. Day-ahead Scheduling Model*

The total demand of a consumer $u$ at any 30 minute time interval $h$ is the sum of the individual appliances' power consumption in that time period. The consumers communicate with the central entity and exchange power ratings, time limits of appliance operation, and other user constraints such as preferred indoor temperature. The central entity runs an optimization algorithm and sends the schedule of the appliances for the next day to the local controller. The day-ahead schedule is determined with a view to optimize energy usage without a compromise in comfort, thereby minimizing the cost incurred by the consumer. The objective function for the day-ahead schedule can be represented as in (1), and the constraints are in (2).

$$min \quad \sum_{h\in\mathbb{H}} \left( \sum_{m\in\mathbb{M}} \gamma_{u,m}^{h} P_{u,m}^{h} + \sum_{n\in\mathbb{N}} \gamma_{u,n}^{h} P_{u,n}^{h} - P_{u,l}^{h} \right) k_{G}^{h} + \phi_u \sum_{h\in\mathbb{H}} \left( t_{u,set}^{h} - t_{u,req}^{h} \right) \tag{1}$$

$$\sum_{h=\psi}^{\omega} \gamma_{u,m}^{h} P_{u,m}^{h} = \mathcal{E}_m, \qquad \forall u, m \tag{2a}$$

$$\sum_{h=\psi}^{\omega} \gamma_{u,n}^{h} P_{u,n}^{h} = \mathcal{E}_n, \qquad \forall u, n \tag{2b}$$

$$\sum_{m\in\mathbb{M}} \gamma_{u,m}^{h} P_{u,m}^{h} + \sum_{n\in\mathbb{N}} \gamma_{u,n}^{h} P_{u,n}^{h} \geq 0 \tag{2c}$$

$$\gamma_u^h \geq 0; \qquad \forall h \in [\psi, \omega] \tag{2d}$$

$$= 0; \qquad otherwise \tag{2e}$$

$$\mathcal{P}_{min} \leqslant P_{u,m}, P_{u,n} \leqslant \mathcal{P}_{max} \tag{2f}$$

$$t_{min} \leq t_{u,set}, t_{u,req} \leq t_{max} \tag{2g}$$

where $m$ and $n$ represent the shiftable and the base loads, $P_{u,m}$ and $P_{u,n}$ represent their power consumption, $E_{u,m}$ and $E_{u,n}$ is the energy consumed and $P_{min}$ and $P_{max}$ are the minimum and maximum power levels, respectively. $\psi$ and $\omega$ are the preferred start and end operating times of shiftable loads and $\gamma$ is the binary optimization variable for appliance operation. $P_{u,l}$ is the onsite power produced, and $k_G$ is the price of power procured from the grid. $t_{u,req}$ and $t_{u,set}$ are the requested indoor temperature and the controller-provided indoor temperature, respectively, and $\phi_u$ is the dissatisfaction cost which converts changes in temperature to monetary units. The dissatisfaction cost is fixed for every user. The unit of $\phi$ is \$/°C.

The first two constraints: (2a) and (2b) limit the energy consumption of the appliances to the maximum energy consumption per appliance. The power balance in (2c) ensures that excess energy of electric vehicles and storage devices is not fed into the grid due to low feed-in tariff. (2d) and (2e) set the constraints for binary optimization variables to ensure that appliances only operate during the desired operating timeframe set by the consumer. The optimization bounds for the appliance power consumption and the indoor temperature are represented in (2f) and (2g). It is assumed that the consumers follow the schedule sent from the controller. These schedules are also shared with the CSF entity, which helps the entity maximize profits the next day.

### *3.2. Electricity Purchase Cost*

The electricity cost for each user $u \in \mathbb{U}$, depends on the power purchased from the grid, the CSF and the neighbors. The cost of various power sources helps every consumer select the source that minimises the energy purchase cost. Assigning a cost to on-site produced power helps other consumers $d \in \mathbb{U} \neq u$ make an informed decision on the whether to procure power from neighbors. So at any time $h \in \mathbb{H}$ the total cost incurred by any consumer $u$ to procure power can be defined as in (3).

$$\$_u^h = P_{u,G}^h k_G^h + k_{u,p}^h P_{u,p}^h + k_{u,b*}^h P_{u,b*}^h \tag{3}$$

where $\alpha$ and $\beta$ are the percentage preferences of prosumer $u$ to purchase power from the CSF and the peers respectively. $P_{u,G}$ is the power acquired from the grid at a cost of $k_G$, $P_{u,p}$ is the power procured from the peers at a cost of $k_{u,p}$, and $P_{u,b*}$ is the power acquired from the CSF battery at a cost of $k_{u,b*}$.

### *3.3. Cost of CSF power*

The price at which the CSF can provide power to consumers can be characterised by the convex function (4) as in [25]. Quadratic equations are commonly used to model utility functions when there is limited insight into the actual cost functions of consumers. Since the CSF can store power, it is assumed that as demand increases the cost also increases.

$$k_{CSF}(P_{CSF}) = a_{CSF} P_{CSF}^2 + b_{CSF} P_{CSF} + c_{CSF} \tag{4}$$

where $k_{CSF}$ is the cost of power sold to prosumers by the CSF and is a function of the power sold from the battery $P_{CSF}$. $a_{CSF}, b_{CSF}$ and $c_{CSF}$ are constants depending upon the CSF entity preferences such as PV generation, user load profile and grid power price.

### *3.4. Cost of peer surplus power*

Every prosumer $u$, during each time interval $h$, behaves independently to maximise its welfare. Consumers sell off their surplus energy to their neighbors, the CSF or the grid.

Since the consumers do not have batteries installed, the only option to use surplus power is to trade it in the market. The energy-sharing profiles among peers are cleared locally, which means each prosumer can sell energy to any other consumer at a price mutually agreeable to both parties. A non-decreasing quadratic utility function with a marginal benefit that measures consumer willingness to sell a certain amount of energy as in [26] is used in this paper. The cost function for any prosumer, with a total surplus power $P_{-p}$ can be defined as

$$k_p(P_{-p}) = \begin{cases} -\sigma_p {P_{-p}}^2 + \tau_p P_{-p} & ; P_{-p} < \frac{\tau_p}{2\sigma_p} \\ \frac{\tau_p^2}{2\sigma_p} & ;\ otherwise \end{cases} \tag{5}$$

where $\sigma_p$ and $\tau_p$ are constants that vary upon the seller constraints such as the load profile. The power that can be procured by any consumer, $u$ from a seller $p \in \mathbb{U} \neq u$, is bounded by the power consumed by the base loads as the lower limit and the total load at any time $P_{u,load}$.

$$P^h_{u,n} \leq P^h_{u,p} \leq P^h_{u,load} \tag{6}$$

### 3.5. Consumer utility function and revenue

The satisfaction level of consumers can be modelled by a utility function that reflects user preferences over offered goods and services. The goods and services in a P2P trading scenario represent consumer satisfaction from procuring a certain amount of energy from a certain source while maintaining user comfort constraints. Every prosumer, $u \in \mathbb{U}$, has objectives with multiple constraints. Each user has their own preferences such as comfort, RES utilization, etc. Therefore, the consumer utility function reflects the preferences of the consumer such as cost reduction, increase in RES usage and comfort.

The primary objective of the consumer is to minimize the cost of purchased electricity and to maximize their comfort. Every consumer may have preferences that have to be reflected in the utility function. For example, a user may feel it is preferable to purchase CSF power compared to surplus power from neighbors. These preferences are denoted using percentage weighing factors $\alpha$ and $\beta$ for the power procured from the peers and the CSF, respectively. The utility function of a consumer can then be defined as the sum of different objectives i.e. increased utilization of peer surplus power, CSF power and comfort and decreased grid dependency and can be defined as in (7).

$$UF_u = \alpha_u \sum_{h\in\mathbb{H}} P^h_{u,p} k^h_{u,p} + \beta_u \sum_{h\in\mathbb{H}} P^h_{u,b*} k^h_{u,b*} + \sum_{h\in\mathbb{H}} \phi^h_u - \sum_{h\in\mathbb{H}} \$^h_u(P,k) \tag{7}$$

The first term of the utility function maximizes the power utilization from the surplus PV power from the neighbors, and the second term maximises the power procured from the battery maintained by the CSF entity. The maximization of RESs minimizes the cost incurred by the consumer. The final term is the cost paid by the consumer to purchase electricity, and hence it is negative. Every consumer's is willingness to pay for RES utilization can be expressed as in (8).

$$wtp^h_u = k^h_{u,G} + \alpha^h_u k^h_{u,p} + \beta^h_u k^h_{u,b*} \tag{8}$$

Every consumer pays $\$_{RES}$ for the renewable power procured either from peers or the CSF. The total consumer revenues if all the loads are satisfied only by the RESs can be defined as in (9). This addresses changes from resulting RES generation compared to $P_{u,G}$.

$$\$_{\mathbb{U}} = \sum_{h\in\mathbb{H}} \sum_{u\in\mathbb{U}} \left( wtp^h_u - \$^h_{u,RES} \right) \left( P^h_{u,b*} + P^h_{u,p} \right) \tag{9}$$

*3.6. CSF Entity Revenues*

The entity that maintains the CSF may be a group of consumers or a third party. The revenues for the CSF entity are obtained by trading power to the energy-deficient consumers and selling the surplus power to the grid. The initial investment costs for the CSF are included as a fixed cost while calculating per-unit power procured from the CSF. The CSF entity is defined by a financial objective to maximize revenues. Since the CSF entity has only the financial objective of increasing its revenue, the consumers willing to pay higher prices may be dispatched more power. The revenues of the entity without considering the investment cost are defined by (10).

$$\$_{CSF} = \sum_{h=1}^{\mathbb{H}} \left\{ \sum_{u=1}^{\mathbb{U}} \beta_u k^h_{u,b*} P^h_{u,b*} \right\} + k^h_{MCP} P^h_{b\to G} \tag{10}$$

## 4. Optimization Models

### *4.1. Consumer and CSF Revenues*

The initial optimization model aims to maximize the profits of the consumers and the CSF entity. The CSF entity sells the surplus power from the battery to the grid at the MCP. The function optimizes the battery power allocation to the consumers considering the consumer and CSF entity revenues as in (11).

$$\max_{P,k} \quad \$_u + \$_{CSF} \tag{11}$$

$$s.t. \quad P^h_{u,G} + P^h_{u,p} + P^h_{u,b*} + P^h_{u,l} = P^h_{u,load} \tag{11a}$$

$$\sum_{u \in \mathbb{U}} P^h_{u,b*} + P^h_{b\to grid} = P^h_b \tag{11b}$$

$$SOC^h = SOC^{h-1} + \eta_b P^h_{b^{in}} - \frac{P^h_{b\to G}}{\eta_b} - \sum_{u \in \mathbb{U}} \frac{P^h_{u,b*}}{\eta_b} \tag{11c}$$

$$\sum_{u \in \mathbb{U}} P^t_{u,b*} + P^h_{b\to G} \leq SOC^h \tag{11d}$$

$$SOC^h = SOC^{initial} \quad \forall h \in \mathbb{H} \setminus \{0, \mathbb{H}\} \tag{11e}$$

$$0 \leq P^h_{b^{in}} \leq P_{b^h} \tag{11f}$$

$$SOC_{min} \leq SOC^h \leq SOC_{max} \tag{11g}$$

$$P_G, P_p, P_l, P_{load}, P_{b^{in}}, P_{b*}, SOC \in \mathbb{R}^+ \quad \forall \mathbb{H}, \mathbb{U} \tag{11h}$$

where (11a) is the power balance equation between generation and consumption for all time periods. (11b) limits the battery discharge to the total available battery power, and (11c) to (11g) constrains the battery to the charge and power limits. The pricing schemes for the grid power, battery power and the power procured from neighbors result in a financial settlement. The above optimization model reaches equilibrium when the resource is optimally allocated among consumers. The choice of pricing schemes for the grid, CSF and peer generated power determines the revenues shared among the CSF entity and the consumer. The pricing schemes also indirectly depend on the grid tariff. The price of battery power and power procured from the neighbors follows (4) and (5).

### *4.2. Bi-level optimization*

The bi-level model is devised as a game in which the CSF entity is the leader of the Stackelberg game, and the consumers are the followers. The CSF entity, having knowledge about the user load profiles and willingness to pay, can take decisions and try to increase its revenue. The upper level of the bi-level optimization model tries to maximize the CSF revenues, while the lower level maximizes the consumer utility function. The upper-level problem includes the same constraints as in (11). The CSF dispatches energy to the consumers at different prices, either at the consumers' willingness to pay or at a price that varies quadratically with the demand. The lower level problem is continuous and linear.

In the consumer utility function maximization problem, the intersection of the best responses in the Nash equilibrium point of the game maximizes the utility function of each consumer with respect to the strategies of other consumers. The consumer will generate the minimum revenue if their willingness to pay for the RES consumption is equal to the cost of RES procurement from the CSF and the neighbor. Since the CSF entity is fully aware of the consumer preferences, schedules and local RES production, they can calculate the consumers' willingness to pay for energy procurement. The CSF entity maximizes revenues by selling electricity to consumers and the grid, and, having prior knowledge of the demand of consumers, sets the price for CSF-produced power. The bi-level optimization reaches Stackelberg equilibrium, if the consumers and the CSF entity attain optimality. Therefore, if the CSF agent finds the optimized cost and the consumers satisfy their consumption, the model reaches its optimal solution. As the CSF agent is the leader of the game, it is able to exercise market power. If the RES pricing is the same as the consumers' Willingness to Pay (WTP), the consumer with the highest WTP gets the most surplus energy generated by the DERs and hence the payment for procuring surplus DER energy will be higher for that consumer. The allocation of energy will also follow the same pattern i.e. from the highest WTP to the lowest.

$$\max_{P,k} \quad \$_{CSF} \tag{12}$$

$$s.t. \quad k^h_{u,b*} = k^h_{u,CSF} \;\;||\;\; k^h_{u,RES} \tag{12a}$$

$$\text{(11b) - (11g)} \tag{12b}$$

$$k_{b*}, P_{b*}, P_{b^{in}} \in \mathbb{R}^+ \quad \forall \mathbb{H}, \mathbb{U} \tag{12c}$$

$$\max_{P,k} \quad UF^h_u \tag{12d}$$

$$s.t. \quad \text{(11a)} \tag{12e}$$

$$P_{G*}, P_{b*}, P_p \in \mathbb{R}^+ \quad \forall \mathbb{H}, \mathbb{U} \tag{12f}$$

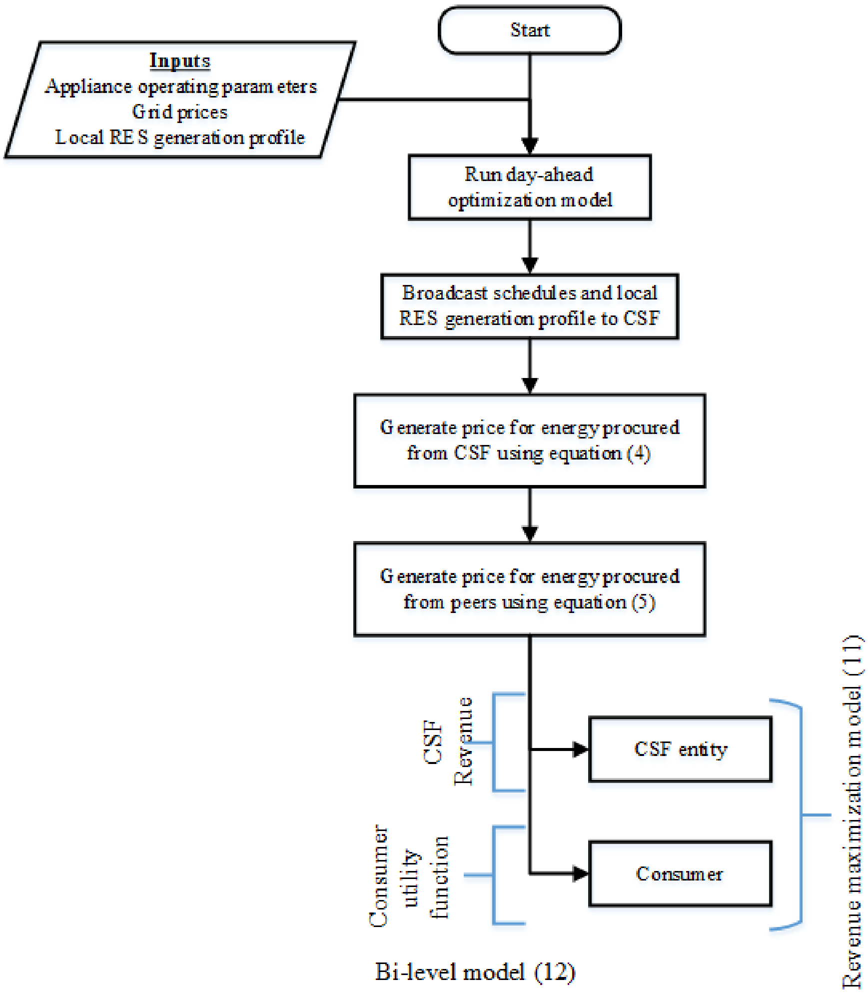



**Figure 2:** Flowchart depicting the sequence of events

Any linear and continuous model can be replaced by KKT conditions by using Lagrangian functions. Therefore, the consumer utility function can be represented by KKT functions as in (13) and (14).

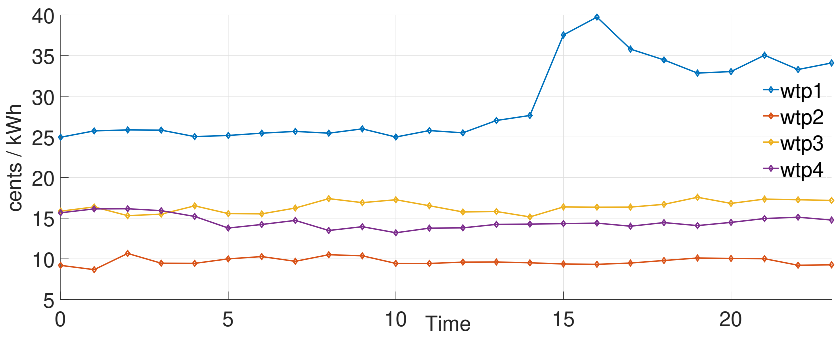
$$
\begin{aligned}
&\mathbb{L}'(P^t_{u,G}) = k^t_{u,G} - \epsilon^t_{u,load} - \epsilon^t_{u,G_{min}} = 0 \\
&\mathbb{L}'(P^t_{u,d}) = k^t_{u,d} - \epsilon^t_{u,load} - \epsilon^t_{u,d_{min}} = 0 \\
&\mathbb{L}'(P^t_{u,b*}) = k^t_{u,b*} - \epsilon^t_{u,load} - \epsilon^t_{u,b*_{min}} = 0 \\
&\mathbb{L}'(\epsilon^t_{u,load}) = P^t_{u,G} + P^t_{u,d} + P^t_{u,b*} - P^t_{u,load} = 0
\end{aligned} \tag{13}
$$

$$
\begin{aligned}
\mathbb{L}\big(P^t_{u,G}, P^t_{u,d}, P^t_{u,b*}, \epsilon^t_{u,load}, \epsilon^t_{u,G}, \epsilon^t_{u,b*}\big) = -\sum_{h=1}^{\mathbb{H}} P^t_{u,G} k^t_{u,G} - \sum_{h=1}^{\mathbb{H}} P^t_{u,d} k^t_{u,d} \\
-\sum_{h=1}^{\mathbb{H}} P^t_{u,b*} k^t_{u,b*} - \epsilon^t_{u,load}\big(P^t_{u,G} + P^t_{u,d} + P^t_{u,b*} - P^t_{u,load}\big) \\
-\epsilon^t_{u,G_{min}} P^t_{u,load} - \epsilon^t_{u,d_{min}} - \epsilon^t_{u,b*_{min}}
\end{aligned}
\tag{14}
$$

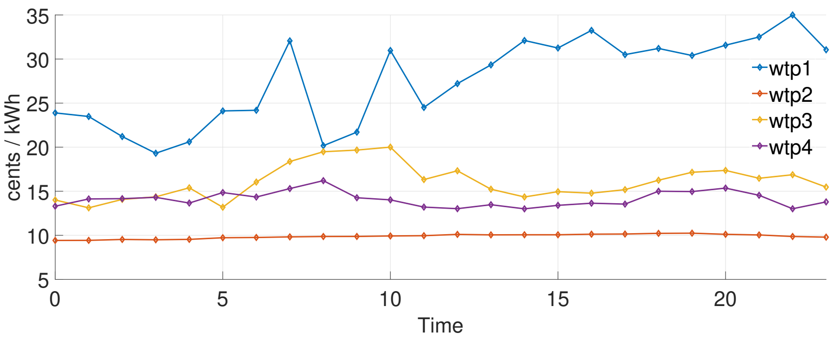
## 5. Simulation Settings

In this section, we evaluate the performance of the optimization algorithms for allocating energy between consumers and the revenue generation with different grid pricing schemes. A smart neighborhood with $\mathbb{U} = 10$ consumers is considered. The usage pattern of a subset of $\mathbb{U}$ represents a residential load profile, so that they have peak demands during the early and late hours of the day. The remaining consumers have a load profile that results in higher power consumption all through the day. Consumers participate in DSM since the shiftable loads are continuous and their energy consumption profile can be adjusted according to the real time tariff set by the energy provider. For the sake of simplicity it is considered that four consumers take part in the energy trading with the CSF and the neighbors. All consumers have PV systems installed, but none have storage onsite. The consumers' electric load includes heating, ~~a~~ ventilation, and ~~an~~ air-conditioning unit~~s~~ (HVAC), electric vehicles, washing machines and dishwashers. Light loads such as lighting, televisions and fans are also included. The consumers' demand is generated from the day-ahead schedules using (1). The inputs to (1) are the preferred operating time of appliances and their minimum and maximum power limits. Energy consumption data are obtained by modelling the consumers in EnergyPlus®. A neural network prediction algorithm as outlined in [27], was used to predict the energy consumption of consumers. The data set for the prediction algorithm considered data for the previous 365 days with a resolution of 30 minutes. Since the comfort level of every consumer varies with time and temperature, the air-conditioning system's energy consumption was derived using the artificial neural network prediction model.

The preferences of consumers are characterized by vectors $\alpha$, $\beta$ and $\phi$. $\alpha$ and $\beta$ are expressed in percentages, which in-turn determines the payment of consumers for the energy procured from neighbors and the CSF. We assume the following vectors for $\alpha$ = [1.2, 0, 0.75, 0] and $\beta$=[1.1, 0, 0, 0.5]. Observation of the vectors shows that consumer 1 is ready to pay the highest amount for procuring RES power, while consumer 2 is not interested in RES power. The remaining consumers have different levels of interest in the CSF and the peer




**(a)**




**(b)**

**Figure 3:** Consumers willingness to pay (a) While following the RTP for the grid procured power. (b) While following the flat rate tariff for the grid procured power

surplus power.

---

**Algorithm 1:** Price of RES - Calculated by central entity

---

**Procedure**: Pricing $k^h_{CSF}$;
$h \leftarrow$ *Transaction period*;
$u \leftarrow 0$;
$k_{RES} \leftarrow \infty$;
$\$^h_{CSF} \leftarrow k^h_{MCP}(P^h_{b*} + P^h_{-p})$;
**for** u $\in \mathbb{U}$ **do**
    $k^h_{RES,u} \leftarrow wtp^h_u$
    *Calculate surplus power sold to the grid,* $P^h_{RES \to G}$ ;
    **if** $P^h_{RES \to G} > 0$ **then**
        $\$^h_{RES} \leftarrow \sum_{z \in \mathbb{U}} k^h_{RES,u} P^h_{z,load} +$
        $k^h_{MCP} P^h_{RES \to G}$
    **else**
        $\$^h_{RES} \leftarrow \sum_{z \in \mathbb{U}, \setminus \{u\}} k^h_{RES,u} P^h_{z,load} + k^h_{RES,u}(P^h_{RES \to G} + P^h_{u,load})$
    **end**
**end**
$P^h_{RES \to G} \leftarrow max \ \ (\mathrm{P}^h_{RES \to G})$;
**Update & return** $\$^h_{CSF}, k^h_{RES}$;
**end**

---

The CSF is a combination of a PV system and battery storage. The temperature and the PV profiles used in this paper were simulated using the System Advisor Model (SAM) [28] and the real-time data were obtained from the Australian Government - Bureau of Meteorology [29]. The PV system consists of a 16.08 kWp solar panel installed in an area of 852 m$^2$. Tesla Powerwall 2 batteries with a storage capability of 13.5 kWh and a round trip efficiency of 90% were used as the batteries in this simulation. The grid price is an important factor that affects the allocation of RES power to various consumers. Two prices for the utility power are used in this paper: RTP and the flat rate tariff. The MCP is derived from the real-time price of the Australian Electricity Market Operator (AEMO). The flat rate tariff is assumed to be 23.2 /kWh and a daily supply charge of 96.4 . The price of power procured from the CSF can be calculated through a quadratic equation in (4). This equation decides the cost based on the demand. During higher-demand periods, the cost is high and vice versa for lower-demand periods. The values of the constants are chosen to reflect the CSF entity preferences. The price of peer surplus power is calculated from (5). This is different from the CSF price calculation, as the price reduces with increase in

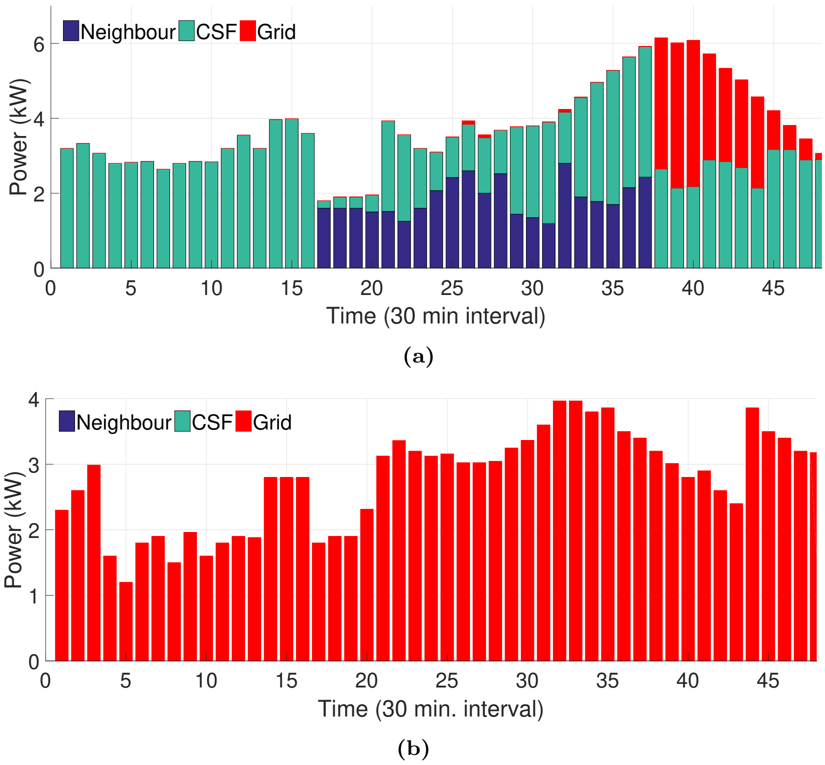
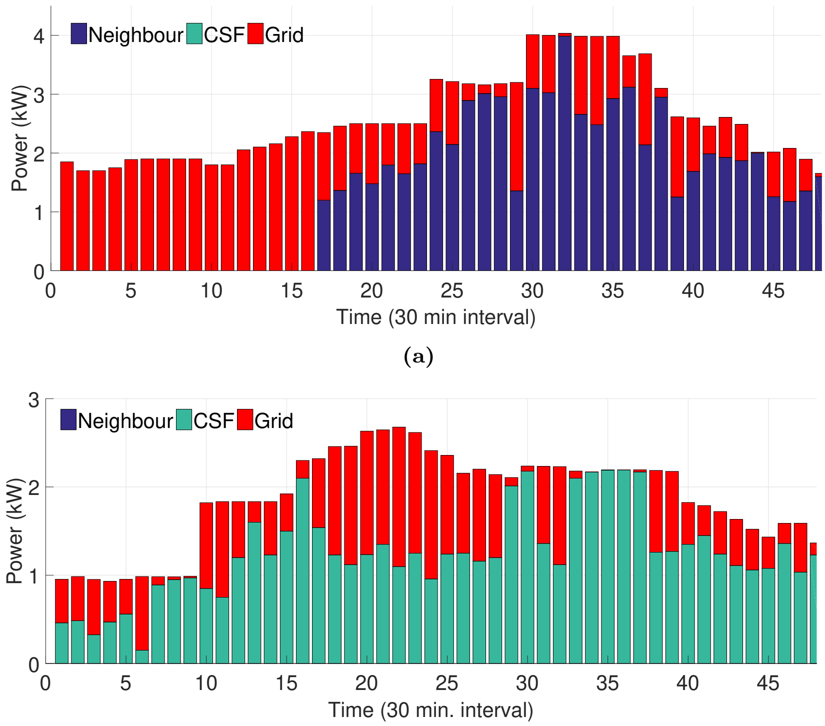



**Figure 4:** Source Allocation (a) Consumer 1 (b) Consumer 2

surplus energy, as the prosumers do not have onsite energy storage systems (ESS). Another pricing scheme followed can be when the consumers are charged based on their willingness to pay for RES power. The third method is to develop an algorithm 1 similar to [18] based on the uniform pricing mechanism. In this algorithm, it is assumed that the CSF entity decides the price of the CSF battery power and the peer surplus power. The CSF entity revenues are updated and the consumers are ranked in descending order of their willingness to pay. Stackelberg equilibrium is reached if the CSF entity can get an optimal solution in-terms of revenue, while consumers can reach optimal solutions in-terms of consumption. When the CSF entity reaches an optimum cost and the consumers find their usage profile, the framework reaches equilibrium. As the CSF entity has prior knowledge of user profiles, it can calculate the WTP of every consumer, and so the entity is in a better position to gain revenue. Since the feed-in tariffs are much below $P^h_{u,g}$, selling CSF or peer surplus power to the consumers is always the best option.




**(a)**

**(b)**

**Figure 5:** Source Allocation (a) Consumer 3 (b) Consumer 4

## 6. Results and Discussion

In this section the simulation results are discussed to show the energy allocation and revenue generation. The demand side management techniques proposed in this work are based on a day-ahead load scheduling model and can be executed locally or by a central controller. Since the demand, RES generation, grid real-time or flat tariffs and usage constraints are shared in advance, the algorithm generates individual appliance usage patterns that reduce the peak load and the cost incurred by consumers. The consumers are willing to pay for their preferences as in Fig. ??. In the first scenario, it is considered that the RES energy from the CSF and the peers are priced according to $k_p$ and $k_{b*}$. The price of peer surplus PV power is inversely proportional to the surplus, since they do not have battery storage. But in the case of CSF power, the cost of power is proportional to the demand due to storage capabilities. In the second scenario, the CSF entity and the neighbors charge consumers according to their WTP. When using this pricing strategy, consumers who are willing to pay excess for RES energy will be given the highest priority by the CSF entity and the peers. In the second scenario consumers 1 to 4 are charged for RESs according to their willingness to pay. In this scenario the consumer revenues in using RESs are 0. In the third scenario, the CSF agent decides on the price of power based on algorithm 1. This algorithm adopted from [18] helps us compare various scenarios presented here. This scenario is more profitable for the CSF agent as he gains more revenue than in the other two scenarios.

Fig. ?? and Fig. ?? show the power allocation of various resources to consumers 1 to 4. As consumer 1 pays the highest cost for the CSF and peer surplus power, most of the time the algorithm allocates RES energy to consumer 1. Since consumer 2 only has comfort as their preference, and since comfort varies with temperature, the grid utilisation of consumer 2 is higher than for many other consumers. Also, the power supplied by the CSF and peers to consumer 2 is zero. Consumer 3 has a higher willingness to pay for the CSF power and hence the CSF is discharged more to consumer 3 than to consumer 4. Also, since consumer 4 is ready to pay more for the peer surplus energy, consumer 4 receives more power from peers.

Fig. 6 and Fig. 8 show the amount of energy dispatched by various sources as well as the energy distributed to consumers for different grid pricing schemes. The CSF entity dispatches the battery either the consumers or the gri to increase the profits. The difference between the RTP and the flat rate is that the RTP offers the consumers better flexibility and hence results in varying resource allocation. The CSF entity sells power to consumers 3 and 4 differently based on their willingness to pay. This occurs due to the changed willingness of the consumers to pay. Since the grid tariff forms a part of the WTP, any changes in the grid price are reflected in the WTP which in turn changes the energy allocation.

Another inference from the results is that the CSF entity discharges more power to the utility and less to consumers with a low WTP. This is because the CSF entity does not want to compromise on revenue generated and is not concerned in minimizing the electricity bills of the consumers or optimal resource allocation. The sharing of welfare between the CSF entity and the prosumers depends on the value of $k_{RES}$. For instance, if the value of $k_{RES}$ is set as the same price as the grid, then the welfare is shared among both parties. The results are summarized in Table 1.

The allocation of the CSF and the pricing schemes adopted influence revenue generation and the distribution of RES power between peers and the CSF entity. The first optimization model maximizes the revenues of the CSF entity and the consumer, but the revenue distribution depends on the pricing scheme adopted. The optimization model finds the optimal pricing for the CSF entity. The consumers are less flexible and are bound to follow the prices set by the CSF entity. The results show that the CSF entity is not concerned about optimal

**Table 1:** Quantum of energy generated / traded between various parties while following different price schemes

| | $k_{RES}$ | | WTP | |
|---|---|---|---|---|
| | FT | RTP | FT | RTP |
| PV | 138.2 | 138.2 | 138.2 | 138.2 |
| $B_{out}$ | 12.34 | 19.62 | 18.29 | 23.46 |
| $B_{in}$ | 24.89 | 23.56 | 28.36 | 20.2 |
| Con. 1 | 122.92 | 118.08 | 96.13 | 117.06 |
| Con. 2 | 0 | 0 | 0 | 0 |
| Con. 3 | 59.32 | 68.03 | 27.46 | 40.36 |
| Con. 4 | 64.89 | 58.63 | 47.76 | 52.63 |

**Table 2:** Welfare results using the initial framework model for different grid pricing scenarios

| $Pricing$ | $k_{b*}, k_p$ | | $Saving$ |
|---|---|---|---|
| | $Flat$ | $RTP$ | |
| $Consumer$ | 6.8 | 8.32 | 22.3% |
| $CSF$ | 23.672 | 25.06 | 5.8% |

energy allocation and focuses only on revenue generation. Nevertheless the total benefit of implementing the bi-level model resulted in increased revenues.

Tables 2 and ?? shows the revenues of the CSF entity and the consumers taking part in the trading. Both tables show that revenue generation is improved when the real-time grid prices are followed. As expected when using the initial model, resource allocation precedes revenue generation. Hence, the revenues generated by the CSF is less than the revenue generated from the bi-level model. The consumer revenue while using the RTP increased by 81.9% compared to the flat tariff while the CSF revenue increased around 10.55%. The consumer revenues improved due to the fact that, during the high-price periods using RTP, consumers preferred to use RES energy either from the CSF or the peers. On the contrary the CSF entity saw only a marginal increase in revenues. If the consumers are charged at their willingness to pay, the CSF entity sees a fall in revenue generated, and the percentage difference between the two pricing schemes of the grid is 7.15%.

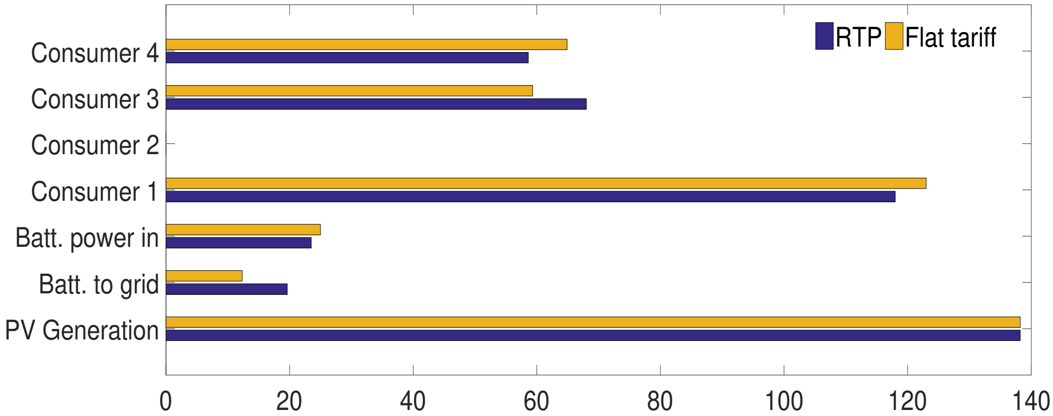



**Figure 6:** RES consumption / generation by various consumers / sources while following the RTP and fixed rate grid pricing using Algorithm 1

**Table 3:** Welfare results for the bi-level model for different grid pricing scenarios

| $Pricing$ | $k_{RES}$ | | | $wtp_u$ | | |
|---|---|---|---|---|---|---|
| | $Flat$ | $RTP$ | $Savings$ | $Flat$ | $RTP$ | $Savings$ |
| $Consumer$ | 2.1 | 3.82 | 81.9% | 0 | 0 | 0 |
| $CSF$ | 36.2 | 40.02 | 10.55% | 32.3 | 34.6 | 7.15% |

### *6.1. Economic Viability*

Prosumers take part in demand side management or energy sharing if it is profitable and if the capital invested will be paid back in a short span of time. The Net Present Value (NPV) is used to analyse the profitability of a projected investment or project. In this paper we ~~use~~ calculate the NPV of the total cost of installation of the solar photo-voltaic system. If the NPV is positive, the investor makes a profit and the payback period can be calculated.

Initially an NPV of the savings in the cost of power in using renewable energy is calculated. The NPV of the savings in the cost of power procured from the grid can be calculated as in 15.

$$NPV_s = Y\frac{\left(1-\left(1-r\right)^{-n}\right)\right)}{r} \tag{15}$$

where $r$, the discount rate, is the expected rate of return the consumer could earn for a similar risk in financial markets. $Y$ is the cash flow as a result of using the solar photo-voltaic system and $n$ is the time period when the prosumer that pays the capital costs accrues benefits from the savings due to the use of renewable energy. The total NPV can be calculated from $NPV_s$ using equation 16.

$$NPV_t = NPV_s - C \tag{16}$$

where C is the installation cost. Because inflation affects the cost of borrowing money and the cost of energy, they cancel each other out and therefore do not need to be accounted for. Therefore, the future costs are based on the sum of the future load, future energy costs and discount rate. The payback period $N$, as defined in 17, is time taken (in years) for the total NPV to reach zero.

$$N = \frac{-\log\left(1 - \left(\frac{rC}{Y}\right)\right)}{\log(1+r)} \tag{17}$$

Fig. 7 compares the payback period of prosumers sharing power with the community and with the power grid. The plots clearly show that the payback period is less when power is traded in the community. This is due to the low feed in tariffs for the grid and the profits made by prosumers in the CEMS. The CSF entity takes a longer time to pay off since their investment costs are high and their running costs are low. Prosumer 3 has the lowest payback period since they can trade considerable power with the peers, the CSF or the grid.

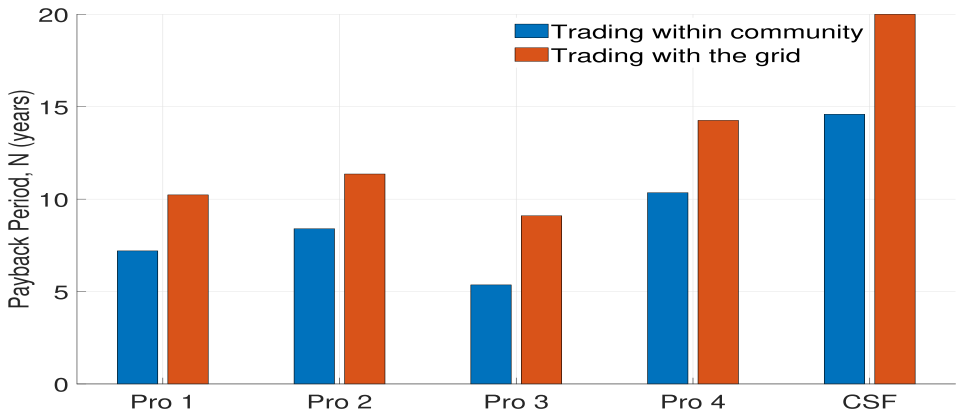



**Figure 7:** Payback period of various prosumers and the CSF entity

## 7. Conclusion

The CEMS framework presented in this paper facilitates local P2P trading among consumers in a community, a common storage facility owned by the community, and the power grid. The initial day-ahead optimization provides the prosumer with an energy consumption pattern to minimize the cost of power procured from the grid. This paper compares two energy trading models for the CEMS. In the initial model the welfare is shared among the CSF entity and prosumers depending on the pricing strategies followed. The bi-level model maximizes the CSF entity revenues by setting prices according to the WTP of the prosumers. Hence, revenue generation has more priority than the optimal energy allocation. Consumers' utility functions are characterised by their preferences such as RES usage and comfort.

Both models yield the same result if the CSF and peers charge the consumers according to their willingness to pay. So the consumers with the highest WTP are prioritised and hence the model is efficient in revenue generation and optimal resource allocation. The pricing schemes determine how the revenues are shared between various participating entities. The bi-level model acts as an incentive for investments in the CSF. The proposed model is evaluated for a residential community in Sydney, Australia. Simulations based on real-life data indicate that prosumers achieve revenue if they are not charged by their WTP, and the revenues can be as high as 82% while following the RTP. As for the CSF entity, they see an increase of 10.55% during the RTP scenario compared to the flat rate scenario.

### *7.1. Limitations and Future Work*

The CEMS models require large amount of data exchange that can provide insights into the energy consumption patterns of consumers. This might lead to privacy concerns and eventually restrict consumers from sharing data and participating in the local energy market. Hence, a fine balance between privacy and economic benefits must be attained, and this can be achieved through suitable changes in legislation. The pricing schemes must be developed taking into account the behavior of the community in which it is implemented. Hence, pricing schemes that fits one community may not be suitable for another community. This is because consumer behavior is highly unpredictable. Consumer energy usage varies with region, culture, race and many other geophysical parameters. A fair assumption of the behavior of consumers can be deduced from their previous electricity consumption patterns. Another issue is consumers not adhering to the consumption pattern set by the controller. This can lead to a mismatch in the energy traded and hence bring losses to the prosumers. This can be avoided by introducing penalty functions, which will act as a deterrent.

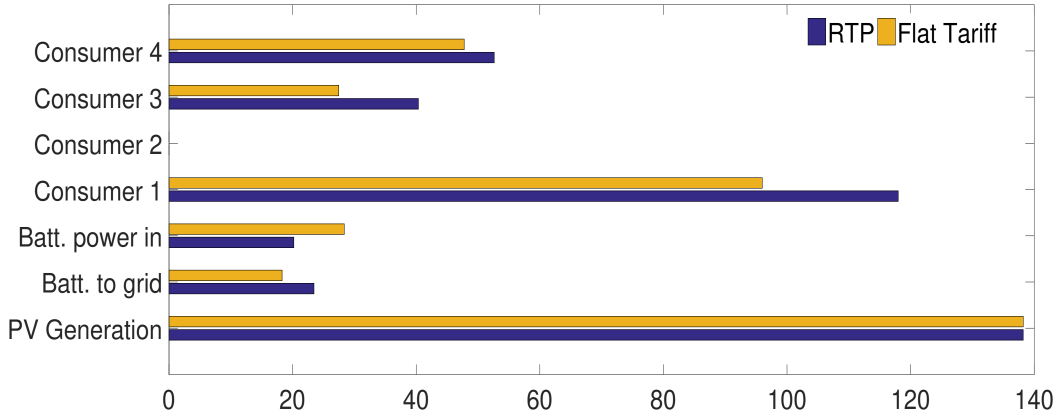



**Figure 8:** RES consumption / generation by various consumers / sources while following the RTP and fixed rate grid pricing using consumers WTP

Future work should consider investment costs, uncertainties in RES power production and user behavior. The effects of various communication protocols, and their resiliency and the effects of communication delays and packet losses ~~can lead to a robust system.~~ Furthermore, all algorithms and data handling can be implemented on a cloud-based platform which centralizes computation and is cost effective.

### 7.2. *Applicability to Real World Scenario*

This section discusses the adaptability of the proposed algorithms to real-world scenarios. The proposed models in this paper can be extended to include any type of consumers. For large consumers such as industries, the pricing models can include installation and upfront costs, grid tariffs, network costs and tax credits, as these will play a significant part in deciding the price of energy traded. Although this study considers only PV models as the renewable energy source, it can be replaced or coupled with any other source such as wind power systems to adapt to any environment. The consumer smart appliances could be connected to a smart meter via a Zigbee gateway which can store all incoming data that can be used for processing. The Zigbee gateway can send all necessary information to a home controller which could be a Raspberry Pi, Arduino or a Teensy 3 micro-controller. These controllers are cheap, easy to install and executes computation quickly.

Another technology that can be applicable to energy management is data processing using cloud-based applications. The Message Queuing Telemetry Transport (MQTT) protocol, is light weight, fast and reduces the power consumption of network devices. Several free Internet of Things (IoT) platforms such as ThinkSpeak can help in the collection and processing of meta data via a local area network (LAN). Many of these IoT platforms can host optimization software such as Matlab or GAMS. Cloud-based applications are reliable when large amount of data transfer are involved. This can be a huge source of cost saving for consumers, especially larger consumers, as they will already be using the cloud for other regular business activities.

## References


[1] Ceglia, F and Esposito, P and Marrasso, E and Sasso, M, From Smart Energy Community to Smart Energy Municipalities: literature review, agendas and pathways, Journal of Cleaner Production (2020).

[2] T. Sousa, T. Soares, P. Pinson, F. Moret, T. Baroche, E. Sorin, Peer-to-peer and community-based markets: A comprehensive review, Renewable and Sustainable Energy Reviews 104 (2019) 367–378.

[3] Hawlitschek, Florian and Teubner, Timm and Gimpel, Henner, Consumer motives for peer-to-peer sharing, Journal of Cleaner Production 204 (2018) 144–157.

[4] M. Khorasany, Y. Mishra, G. Ledwich, Hybrid trading scheme for peer-to-peer energy trading in transactive energy markets, IET Generation, Transmission & Distribution 14 (2) (2019) 245–253.

[5] T. Morstyn, M. D. McCulloch, Multiclass energy management for peer-to-peer energy trading driven by prosumer preferences, IEEE Transactions on Power Systems 34 (5) (2018) 4005–4014.

[6] R. Rana, S. Bhattacharjee, S. Mishra, Energy trading framework for electric vehicles: an assignment matching-theoretic game, IET Smart Grid 2 (3) (2019) 371–380. `doi:10.1049/iet-stg.2019.0013`.

[7] J. Kang, R. Yu, X. Huang, S. Maharjan, Y. Zhang, E. Hossain, Enabling localized peer-to-peer electricity trading among plug-in hybrid electric vehicles using consortium blockchains, IEEE Transactions on Industrial Informatics 13 (6) (2017) 3154–3164. `doi:10.1109/TII.2017.2709784`.

[8] Daneshvar, Mohammadreza and Pesaran, Mahmoud and Mohammadi-ivatloo, Behnam, Transactive energy integration in future smart rural network electrification, Journal of Cleaner Production 190 (2018) 645–654.

[9] M. Selvan, S. L. Arun, H. Rao, et al., Framework of locality electricity trading system for profitable peer to peer powertransaction in locality electricity market, IET Smart Grid (2020).

[10] B. H. Rao, S. L. Arun, M. P. Selvan, An electric power trading framework for smart residential community in smart cities, IET Smart Cities 1 (2) (2019) 40–51.

[11] N. Liu, X. Yu, C. Wang, C. Li, L. Ma, J. Lei, Energy-sharing model with price-based demand response for microgrids of peer-to-peer prosumers, IEEE Transactions on Power Systems 32 (5) (2017) 3569–3583. `doi:10.1109/TPWRS.2017.2649558`.

[12] C. Long, J. Wu, Y. Zhou, N. Jenkins, Peer-to-peer energy sharing through a two-stage aggregated battery control in a community microgrid, Applied energy 226 (2018) 261–276.

[13] C. Zhang, J. Wu, Y. Zhou, M. Cheng, C. Long, Peer-to-peer energy trading in a microgrid, Applied Energy 220 (2018) 1–12.

[14] M. Alam, S. Ramchurn, A. Rogers, Cooperative energy exchange for the efficient use of energy and resources in remote communities (2013).

[15] F. Ahmadi, A. Akrami, M. Doostizadeh, F. Aminifar, Energy pricing and demand scheduling inretail market: How microgrids integrationaffects the market, IET Smart Grid (2020).

[16] A. Alahäivälä, M. Ali, M. Lehtonen, J. Jokisalo, An intra-hour control strategy for aggregated electric storage space heating load, International Journal of Electrical Power & Energy Systems 73 (2015) 7–15.

[17] X. Wu, X. Hu, X. Yin, S. J. Moura, Stochastic optimal energy management of smart home with pev energy storage, IEEE Transactions on Smart Grid 9 (3) (2016) 2065–2075.

[18] A. Fleischhacker, H. Auer, G. Lettner, A. Botterud, Sharing solar pv and energy storage in apartment buildings: resource allocation and pricing, IEEE Transactions on Smart Grid 10 (4) (2018) 3963–3973.

[19] Golpîra, Hêriş and Bahramara, Salah, Internet-of-things-based optimal smart city energy management considering shiftable loads and energy storage, Journal of Cleaner Production (2020).

[20] Banfi, Silvia and Farsi, Mehdi and Filippini, Massimo and Jakob, Martin, Willingness to pay for energy-saving measures in residential buildings, Energy economics 30 (2) (2008) 03–516.

[21] P. Jamborsalamati and E. Fernandez and M. Moghimi and M. J. Hossain and A. Heidari and J. Lu, MQTT-Based Resource Allocation of Smart Buildings for Grid Demand Reduction Considering Unreliable Communication Links, IEEE Systems Journal 13 (3) (2019) 3304–3315.

[22] Feed-in tariff rates, `https://energysaver.nsw.gov.au/households/solar-and-battery-power/feed-tariff-rates`, accessed: 2019-10-25.

[23] M. S. H. Nizami, J. Hossain, Optimal scheduling of electrical appliances and der units for home energy management system, in: 2017 Australasian Universities Power Engineering Conference (AUPEC), IEEE, 2017, pp. 1–6.

[24] H. Von Stackelberg, Market structure and equilibrium, Springer Science & Business Media, 2010.

[25] E. Sorin, L. Bobo, P. Pinson, Consensus-based approach to peer-to-peer electricity markets with product differentiation, IEEE Transactions on Power Systems 34 (2) (2018) 994–1004.

[26] P. Samadi, H. Mohsenian-Rad, R. Schober, V. W. S. Wong, Advanced demand side management for the future smart grid using mechanism design, IEEE Transactions on Smart Grid 3 (3) (2012) 1170–1180. `doi:10.1109/TSG.2012.2203341`.

[27] E. Fernandez, M. Hossain, M. Nizami, Game-theoretic approach to demand-side energy management for a smart neighbourhood in sydney incorporating renewable resources, Applied Energy 232 (2018) 245–257.

[28] National Renewable Energy Laboratory, System Advisor Model (SAM), `https://sam.nrel.gov/content/downloads`, version: 2016.3.14.

[29] Bureau of Meteorology, Australian Government (BOM), `https://http://www.bom.gov.au/nsw/?ref=hdr`.