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GAME THEORY BASED OPTIMAL BATTERY POWER FLOW MANAGEMENT IN A PEER-TO-PEER ENERGY SHARING NETWORK

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ABSTRACT

This paper presents a household battery charging and discharging game for a power supply-demand regulation in a peer-to-peer energy sharing, operating in the day-ahead electricity market. The problem is formulated as a noncooperative Nash equilibrium game where the households are considered selfish but rational players whose objectives are to optimize their individual battery state of charge and energy cost. The application of the proposed model to a practical case study of three households shows the potential of the households to regulate the electricity in the smart grid and save their energy costs. Households 1, 2 and 3 operating in the proposed model saved energy costs of up to 59.8%, 58.8% and 58.9%, respectively compared to them operating in a strictly real-time electricity market and household 1, 2 and 3 also had savings of up to 10%, 3.8% and 8.4%, respectively compared to them operating in a strictly day-ahead electricity market.

Keywords: Day-ahead market, electricity regulation, game theory, peer to peer energy sharing, smart grid

1. INTRODUCTION

Historically, the electrical power generation follows the consumption, however the current rise in economic growth has compromised the supply-demand robustness and efficiency of the electrical grid [1]. The electrical grid can only store a very limited amount of the unused generated electricity; therefore, it must take crucial steps to maintain stability. An unstable supply and demand may cause the power grid frequency to drop and rise out of acceptable margins, instantly damaging the electricity generating turbines and the protective and control equipment in the system, consequently leading to a power grid failure, which is costly for the electrical grid to repair [2]. Therefore, the electrical grid assigns small electrical power systems known as smart grids to different electricity markets as one of the crucial steps. The electricity market which is an electricity division in a municipality enables sales and purchases of electricity through bids and sales offers, governed by the supply and demand principles generally in the form of financial exchanges. Smart grids are electricity supply networks that may consist of multiple distributed energy resources, customers, energy storage units, smart meters and use digital communications technology to detect and react to local changes in usage. Smart grids mainly suffer from electricity supply and load demand unbalance and consequently its frequency may undergo rapid changes. A battery energy storage system due to its very fast dynamic response can play an important role in restoring balance between supply and demand.

Energy storage devices can be employed at the residential level to address the problem of electricity fluctuation [3]. Households are encouraged to charge their batteries using lower energy prices during high-supply-low demand periods and supplying their loads during high-demand low-supply periods. A mixed strategy Nash equilibrium game model in a day ahead market was used to optimize the power quality of the electricity grid and consequently minimize the household electricity bills using a real-time pricing structure that encourages the households to charge their lead acid batteries when there is surplus power and discharge their batteries when there is deficient power supply [4].

The modelled system is an open loop that does not consider periods when households' batteries are unable to charge as they have reached their maximum capacity or when household batteries are unable to discharge as to supply their loads during deficient electricity market power supply for they have reached their minimum capacity.

This study introduces a battery bank backup in the electricity market for the former case and incorporates the peer-to-peer (P2P) energy sharing structure for the latter case. Households participate in the P2P energy sharing structure periods when the household's real-time electricity demand exceeds the electricity forecasted, and the deficient power cannot be met by the electricity market or by the household batteries. The electricity market whose aim is to stabilize the electricity in the smart grid, encourages households to participate in P2P energy sharing by using an electricity tariff that is lower than the time-of-use (TOU) electricity tariff, such that, instead of disturbing the power stability in the smart grid by buying electricity from the electricity market during time periods when neither the household batteries nor the electricity market is able to meet the household's real-time load demand, the households can buy cheaper electricity from their peers. The addition

2. PROBLEM FORMULATION

This study proposes an electricity market regulation household battery charging and discharging in a peer-to-peer energy sharing structure shown in Fig. 1. The smart grid is comprised of an electricity market and households with batteries and smart meters. The electricity market is a profit driven independent agent that operates in a day-ahead market. The electricity market predicts the households' load demand by using smart meters installed at each residential home, essentially to supply only what has been predicted because it buys forecasted electricity from the power grid at lower rates compared to buying unforested electricity.

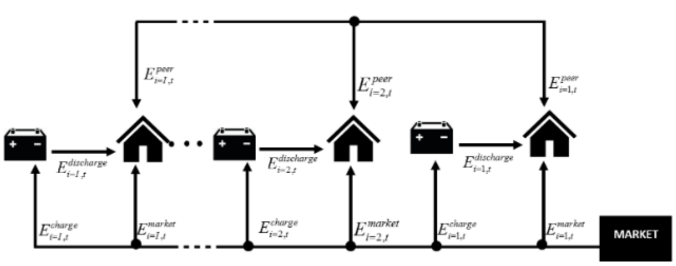


Fig. 1 Schematic layout of the energy flow for the proposed model at time t.

As shown in Fig.1, a household's load demand can be supplied by either the electricity market $E_{i,t}^{market}(kWh)$, the battery, $E_{i,t}^{discharge}(kWh)$, or by its peers, $E_{i,t}^{peer}(kWh)$, depending on how much electricity was predicted by the electricity market and its battery state of charge (SOC). Households charge their batteries from the electricity supplier, $E_{i,t}^{charge}(kWh)$, in an attempt to regulate the supply and demand of electricity market by participating in a game called a mixed strategy Nash equilibrium.

2.1 Day ahead load prediction

For a simplified load forecasting, this study considers the real-time load demand from the previous day, $m_{i,t-T}^{real}$ to be the predicted load demand for household i at time t, $m_{i,t}^{forecasted}\left(kWh\right)$, that is;

$$m_{i,t}^{forecasted} = m_{i,t-T}^{real}, \qquad (1)$$

where, T is the total time periods in a day. This study predicts the load demand at every hour, thus $T = 24$. The predicted load demand is the real-time energy supply, and in real time the electricity market wishes to supply only what was exactly predicted.

2.2 Electricity pricing

The electricity market's aim to balance the real-time electrical load demand $m_{i,t}^{real}$ and the forecasted load demand $m_{i,t}^{forecasted}$ can result in three possible outcomes, perfect supply, undersupply and oversupply. Perfect supply is when the households' real-time load demand matches with their forecasted load demand. Undersupply is when the households' real-time load demand is more than their forecasted load demand. Oversupply is when the households' real-time load demand is less than the forecasted load demand.

2.2.1 Oversupply electricity in the market

In oversupply, the electricity market sells the excess electricity to the households using pricing rate ε_t^{buy} [4], for the purpose of charging their lithium-ion batteries, which were chosen for this study due to their high charging efficiency and long lifespan compared to lead acid batteries.

$$\varepsilon_t^{buy} = TOU_t - \kappa\left(\left(A_t + A_{t-T}\right) - \sum_{i=1}^{I} B_{i,t}^{c}\right), \;\; \kappa > 0, A_t > 0, \qquad (2)$$

The pricing rate $\varepsilon_t^{buy}\left(R/kWh\right)$ that guides the charging behaviour of the households' batteries is derived from the basic principle of a straight-line graph with a negative slope. $TOU_t\left(R/kWh\right)$ is the point where the line graph cuts the y-axis and it represents the grid electricity tariff which the electricity market uses to bill households for using the forecasted load demand at time t, $\kappa\left(R/kWh^2\right)$ is the slope of the line graph and it represents the time-independent charging behavior incentive parameter specified by the electricity supplier, $B_{i,t}^{c}\left(kWh\right)$ is the charging profile of household i at time t, $A_t\left(kWh\right)$ is the surplus or deficient power of the electricity market at time t, given as;

$$A_t = \sum_{i=1}^{I}\left(m_{i,t}^{forecasted} - m_{i,t}^{real}\right). \qquad (3)$$

When $A_t + A_{t-T} = 0$ the market has a *perfect supply* and $\varepsilon_t^{buy}\left(R/kWh\right)$ is equal to $TOU_t\left(R/kWh\right)$. When $A_t + A_{T-t} > 0$, the market has an *oversupply* and $\varepsilon_t^{buy}\left(R/kWh\right)$ is less than $TOU_t\left(R/kWh\right)$, encouraging households to charge their batteries. The households are encouraged by a low charging pricing rate ε_t^{buy} to charge their batteries with $E_{i,t}^{charge}(kWh)$. When $A_t < 0$, the market has an *undersupply* and $\varepsilon_t^{buy}\left(R/kWh\right)$ is greater than $TOU_t\left(R/kWh\right)$, discouraging households from charging their batteries, instead they discharge their batteries to satisfy their load demand. When their batteries cannot satisfy their load, households enter the peer-to-peer energy sharing entity to buy energy from their peers.

2.2.2 Undersupply electricity in the market

The peer-to-peer energy $E_{i,t}^{peer}(kWh)$ is sold by a household using an internal selling rate z_t^{sell} and bought by another household using an internal buying rate, z_t^{buy}. Peer to peer energy sharing internal pricing rates were introduced in [3] and adjusted in [5]. z_t^{buy} and z_t^{sell} have two fundamental principles, 1) the internal prices are bounded by the cost of buying surplus power from the electricity market and the profit households get from selling power to the electricity market, i.e. $\varepsilon_t^{market} > z_t^{buy} > z_t^{sell} > \varepsilon_t^{rate}$ .. 2) The internal prices are a function of supply and demand ratio (SDR). Supply is how much power the households are willing to sell, TSP_t, and demand is how much power is deficient for households unable to meet their load demand, TBP_t, that is $SDR_t = TSP_t\left[TBP_t\right]^{-1}$. The internal prices are given as;

$$z_{i,t}^{buy}\left(SDR_t\right) = \begin{cases} z_{i,t}^{buy}\cdot SDR_t + \varepsilon_t^{market}\cdot\left(1 - SDR_t\right), & 0 \le SDR \le 1, \\ \varepsilon_t^{rate} + \dfrac{\lambda_t}{SDR_t}, & \text{SDR>1,} \end{cases} \qquad (4)$$

$$z_{i,t}^{sell}\left(SDR_t\right) = \begin{cases} \dfrac{\varepsilon_t^{rate}\cdot\varepsilon_t^{market}}{\left(\varepsilon_t^{market} - \varepsilon_t^{rsate}\right)\cdot SDR_t + \varepsilon_t^{rate}}, & 0 \le SDR_t \le 1, \\ \varepsilon_t^{rate} + \dfrac{\lambda_t}{SDR_t\cdot SDR_t}, & SDR_t > 1, \end{cases} \qquad (5)$$

where $\varepsilon_t^{market}(c/kWh)$ represents the rate of buying unforecasted electricity from the electricity market. When the electricity market is in undersupply, $TOU_t < \varepsilon_{i,t}^{buy}$ holds, which violates the first principle. To ensure that the market makes a profit, the rate of buying from the electricity market is given by; $\varepsilon_{i,t}^{market} = TOU_t + \varepsilon_t^{rate}$, where $\varepsilon_t^{rate}(c/kWh)$ represents the rate, selling household have spent for each kWh in the battery, and it is given by, $\varepsilon_{i,t}^{rate} = \varepsilon_{i,t}^{battery}\cdot b_{i,t}^{-1}$,where $\varepsilon_t^{battery}(c)$ is the total cost for the power in the battery and given by; $\varepsilon_{i,t}^{battery} = \varepsilon_{t-1}^{battery} + E_{i,t}^{charge}\cdot\varepsilon_t^{buy} - E_{i,t-1}^{peer}\cdot z_{t-1}^{buy}$. The compensation price $\lambda = \varepsilon_t^{market} - \varepsilon_t^{rsate}$ is introduced, to ensure households are better off when they participate in the energy sharing mechanism.

2.3 Mixed-strategy Nash equilibrium

In this study, a mixed strategy Nash equilibrium was chosen as the optimization problem solver when the electricity market is in oversupply such that households compete to charge their batteries with the surplus electricity. In the mixed strategy players randomize between their strategic actions with a probability that makes their neighbours actions indifferent, meaning that whichever strategic action each player chooses, all the players will reach a Nash equilibrium where no player can improve on his/her payoff by deviating from his/her initial optimal strategy given that the other players stick to their optimal strategies. At every time t, household i has two strategic actions $w_{i,t} = \left(w_{i,t}^{1} = 1, w_{i,t}^{2} = 0\right)$ each with an assigned probability $\alpha_{i,t} = \left(\alpha_{i,t}^{1}, \alpha_{i,t}^{2}\right)$ it can play to get its payoff at Nash equilibrium. The payoff function $\gamma\left(w_{i,t}, w_{-i,t}\right)$ at time t for household i is given by:

$$\gamma\left(w_{i,t}, w_{-i,t}\right) = \begin{cases} \varepsilon_t^{buy} + z_{i,t}^{buy}, & \text{if} \quad w_{i,t} = 1, \\ 0, & \text{if} \quad w_{i,t} = 0, \end{cases} \tag{6}$$

where $w_{i,t}$ denotes the strategy of household i at time t and $w_{-i,t}$ denotes the strategies of all households other than the household i at time t. $w_{i,t} = 1$ represents battery charging for household i at time t, $w_{i,t} = -1$ represents battery discharging for household i at time t, and $w_{i,t} = 0$ represents an idle battery for household i at time t.

2.4 Optimization model

The main objective function of the optimization model is for the electricity market to minimize the difference between the electricity supply and electricity demand in the smart grid. To achieve this, the electricity market satisfies two objectives. Firstly, households charge their batteries when $A_t > 0$.

$$J_C = \min \sum_{t=1}^{T} \left(\sum_{i=1}^{I} B_{i,t} - A_t \right)^2, A_t > 0, \tag{7}$$

Secondly, households discharge their batteries and participate in the peer to peer energy sharing structure to account for any deficiencies unmet by the batteries, when $A_t < 0$.

$$J_D = \min \sum_{t=1}^{T} \left(\sum_{i=1}^{I} \left(\left(B_{i,t} + E_{i,t}^{peer} \right) + A_t \right)^2 \right), A_t < 0, \tag{8}$$

The charging and discharging of the household batteries are incorporated, such that the overall objective function with $B_{i,t}$ as the decision variable is given by;

$$J = J_C + J_D, \tag{9}$$

subject to:

$$B_{i,t}^{MIN} < B_{i,t} < B_{i,t}^{MAX}, \tag{10}$$

$$m_{i,t}^{real} = E_{i,t}^{battery} + E_{i,t}^{market}, \tag{11}$$

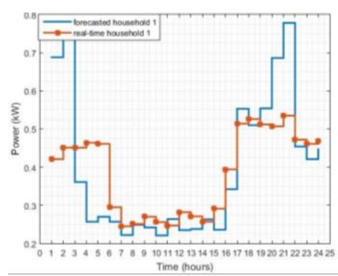
$$B_{i,t} = B_{i,t-1} + E_{i,t}^{charge} - E_{i,t}^{discharge}, \tag{12}$$

$$E_{i,t}^{peer} = m_{i,t}^{real} - m_{i,t}^{forecasted} - B_{i,t}, \text{ if } m_{i,t}^{real} > m_{i,t}^{forecasted}, \tag{13}$$

where $E_{i,t}^{peer}$ represents the deficient energy that was not met by the electricity market and the household battery.

2.5 Case study

The case study uses three randomly selected household load data (household 8, household 77 and household 146) from a pool of 300 household load data [6] collected over the period 1 July 2012–1 July 2013 in Australia. The forecasted demand date was also randomly selected to be on the 31st March 2012 and therefore the real-time data is the load data on the 1st April 2012 as shown in Fig. 2. A 5-kWh lithium ion battery was incorporated for each household, and for the purposes of simulation, the initial battery SOC for household 1, 2 and 3 were respectively randomly generated to be 0.2 kWh, 1.1 kWh and 1.3 kWh. The Australian summer residential Time of use (TOU) tariff [7] was used for electricity consumption.



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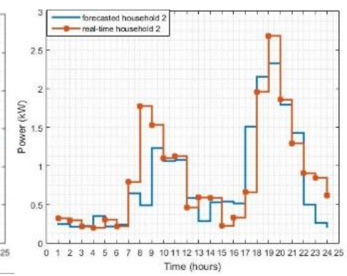

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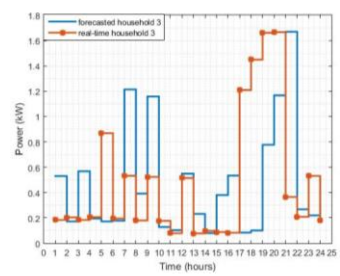


(c)

Fig. 2: Forecasted and real-time load data for a) household 1, b) household 2 and c) household 3

3. RESULTS

The electricity supplier sums the aggregate forecasted load data from all three households at each hour to procure the required electricity in the day-ahead market. The real-time load demand can mismatch the forecasted load demand. Fig. 3 shows the discrepancy between the aggregate real-time load demand and the aggregate load supply. The discrepancy has been rounded off to the nearest charging rate of 0.560 kWh, obtained from the division of the highest absolute discrepancy by the total number of households in the smart grid [2].

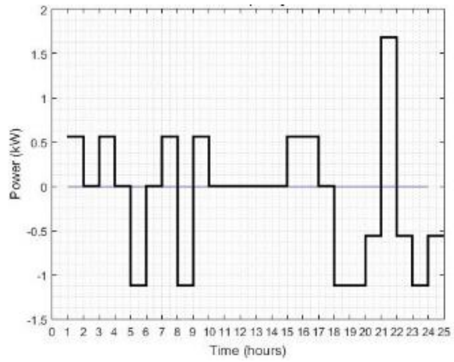


Fig. 3: Discrepancy

When the discrepancy is positive, the households enter the game theory charging game to charge their batteries with the battery charging tariff ε_t^{buy} and when the discrepancy is negative, the households discharge their batteries and purchase energy from their peers with the peer to peer energy buying tariff z_t^{buy}, to supply their deficient loads that were not met by the electricity market or their batteries. It is evident from Fig. 4 that during the time periods when the discrepancy is negative, the battery charging tariff is higher than the TOU tariff and the peer-to-peer energy buying tariff is lower than both the TOU tariff and battery charging tariff to encourage battery discharging and peer-to - peer energy sharing. Similarly, when the discrepancy is positive, the electricity market has surplus power and the battery charging tariff is lower than TOU to encourage battery charging.

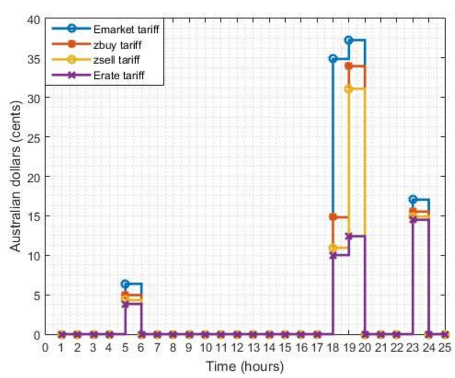
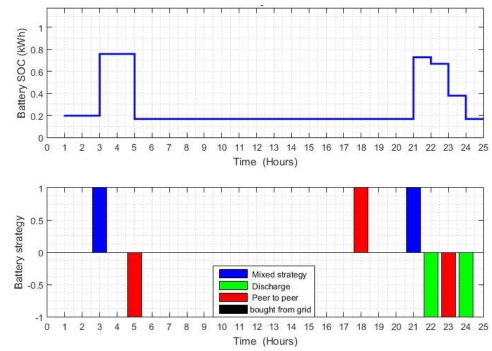


Fig. 4: Energy buying prices

When the discrepancy is positive, the households strategize to increase their battery SOC, and at each hour where $A_t > 0$, a mixed strategy Nash equilibrium was reached, such that no single player can further improve their payoffs by unliterally altering their strategies. The mixed strategies of household 1, 2 and 3 are shown in the bar graphs in Fig. 5, where a battery strategy of 1 represents battery charging.



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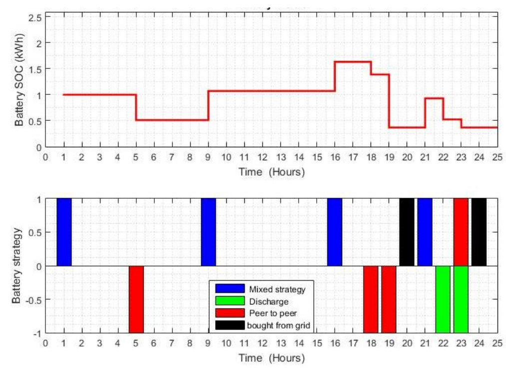

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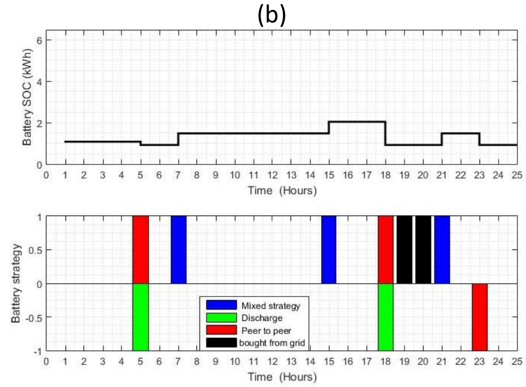
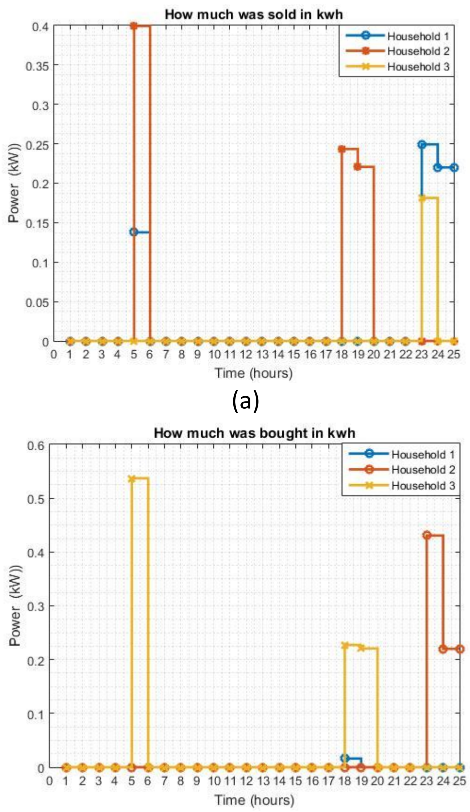


(c)

Fig. 5: Battery SOC and mixed strategy for a) household 1, b) household 2 and c) household 3

Fig. 5 also shows at what time periods each household has discharged its battery to satisfy its load, and what times it has bought energy from its peers when it alone could not satisfy its own load demand. Table 1 shows the energy costs over a 24-hour period each household spent to satisfy their load in different markets using the pricing system in this paper. As stated earlier the pricing systems $TOU_t > \varepsilon_t^{buy} > z_t^{buy} > z_t^{sell} > \varepsilon_t^{sell}$ is met to encourage battery charging and peer to peer energy sharing. Therefore, households in a strictly real-time model, incurred the highest costs. Households in a strictly day-ahead regulation market model also incurred high costs, because when their batteries are unable to meet their load demand, they purchase from the electricity market. Households in the proposed day-ahead regulation market with peer to peer energy sharing incurred the least costs, because when their batteries are unable to meet their load demand, they first purchase from their peers. Figure 6 shows how much households have bought and sold on the P2P energy structure.



(a)

(b)

Fig. 6: Amount of energy (a) sold and (b) bought in the peer to peer energy structure

Table 1 shows the cost of energy for a real-time model with no load forecasting, a load forecasting model without P2P energy sharing and the proposed model that has load forecasting and P2P energy sharing.

Table 1: Households energy cost for 1st April 2012

	Household 1 (AUD)	Household 2 (AUD)	Household 3 (AUD)
Real-time	230.8359	645.6291	426.9627
Day-ahead	103.2236	277.0664	191.5397
proposed	92.9026	266.4137	175.4839

Households 1, 2 and 3 in the proposed model had energy cost savings of 59.8%, 58.8% and 58.9%, respectively compared to them operating in a strictly real-time electricity market and energy cost savings of 10%, 3.8% and 8.4% respectively compared to them operating in a strictly day-ahead electricity market. The energy cost percentage savings were calculated using:

$$\text{Saving}_i(\%)=\frac{\text{Real-time}_i/\text{Dayahead}_i\text{-Proposedmodel}}{\text{Real-time}_i/\text{Dayahead}_i}*100\% \qquad (14)$$

4. CONCLUSION

This paper presented a day-ahead electricity regulation system incorporated with peer-to-peer energy sharing for a smart grid. The objective of the model minimizes the electricity fluctuations in the smart grid by regulating the electricity supply and demand. Households took advantage of these fluctuations to charge their batteries at low energy prices and save their energy costs, The analysis of the results presented in the paper showed the ability for household batteries to regulate the electricity in the smart grid and a huge energy cost saving potential for households by participating in both the day ahead electricity regulation and peer to peer energy sharing. Besides the projected savings, the proposed model creates an extra income stream for the households through the sale of energy in the peer-to-peer energy sharing network.

REFERENCE

[1] Short JA, Infield DG, Freris LL. Stabilization of grid frequency through dynamic demand control. IEEE Transactions on power systems 2007; 22:1284-93.

[2] Wu C, Rad HM, Huang J. Vehicle-to-aggregator interaction game. IEEE Transactions on Smart Grid 2012; 3:434-42.

[3] Long C, Wu J, Yue, Jenkins N. Peer-to-peer energy sharing through a two-stage aggregated battery control in a community Microgri. Applied Energy 2018; 226: 261-76.

[4] Adika C, Wang L. Non-cooperative decentralized charging of homogeneous households' batteries in a smart grid. IEEE Transactions on Smart Grid 2014; 5:1855-63.

[5] Liu N, Yu X, Wang C, Li C, Ma L, Lei J. Energy-sharing model with price-based demand response for microgrids of peer-to-peer prosumers. IEEE Transactions on Power Systems 2017; 32: 3569-3583.

[6] Ratnam EL, Weller SR, Kellett CM, Murray AT. Residential load and rooftop PV generation: an Australian distribution network dataset. International Journal of Sustainable Energy 2017; 36:787-806.

[7] Ausgrid. [Online]. Available: www.ausgrid.com.au/