A Two-Layer Incentive-Based Controller for Aggregating BTM Storage Devices Based on Transactive Energy Concept

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***Abstract*— In this paper, a two-layer controller is proposed to aggregate a fleet of behind-the-meter (BTM) energy storage devices based on the Transactive Energy (TE) concept. In the proposed model, aggregator offers an incentive to consumers to purchase power from and/or sell the excess power back to the grid. To do so, controller at the aggregator's side determines optimal incentive which has to be offered to consumers by maximizing its own profit. Then, local controller at the consumer's location optimizes battery operation by calculating purchased/sold power from/to the grid based on the local demand, PV generation, retail time-of-use (ToU) prices and demand charge, and the incentive offered by the aggregator to maximize its own profit. Different optimization problems are formulated in the two layers, and the profit of aggregator and consumers in the day-ahead energy market under perfect and imperfect prediction scenarios are compared.**

I. Introduction

The total energy bill for commercial/industrial (C/I) loads consists of two parts: Energy and demand charges, which are proportional to the total energy consumption and the peak power consumption, respectively. In some cases, the latter can contribute as high as 50% to the total cost [1]. In order to decrease the demand charge, C/I consumers are encouraged to use controllable behind-the-meter (BTM) storage to purchase energy at a lower cost in order to use it for peak shaving and demand charge reduction. In this regard, several studies proposed control mechanisms to optimally operate on-site storage units [2]–[6]. Despite the storage cost reduction over the last decade, storage technologies (such as Li-Ion batteries) are still very expensive so much so that the investment on energy storage is still a risky one. One way to increase the revenue and consequently reduce the investment risk, is stacked application by participating in the energy and ancillary services markets. However, a single storage cannot meet the requirements to participate in the wholesale energy/ancillary markets. For doing so, a mechanism is needed to aggregate small BTM devices to meet wholesale market operator's requirements.

Recently, several attempts have been made to develop BTM aggregation model [7]–[11]. However, the existing methods mostly rely on the direct access to the BTM devices based on long-term contracts and aggregator's ownership. Here, we propose a strategy for aggregation of BTM devices by means of an optimal price (incentive) signal to each consumer. In this structure, consumers can own the device and participate in the market whenever they wish based on their own profit. The idea is to solve an optimization problem at the aggregator level in which an optimal incentive signal is calculated for each BTM storage device. Then, the incentive signal will be communicated to a local controller at consumers' location to autonomously decide about participation with the offered incentive. The outcome will be higher profit for consumers (by trading energy in the wholesale market through an aggregator) and profit for the aggregator by purchasing power from storage devices at lower price, $c(t)$, and selling it back to the utility at the wholesale market price, $q(t)$. This strategy is designed based on the transactive energy (TE) concept which is expected to be the future of the distribution energy management systems [12], [13]. In this framework, decisions at aggregator's and consumers' levels are made locally; thus, it is scalable. Moreover, consumers only respond to the price signal received from the aggregator as opposed to the wholesale market structure which requires participants to bid in the energy/ancillary markets. Therefore, our mechanism leads to a full automation on the consumers' side which further encourage participation. Also, aggregator can make informed decisions based on the reaction of the participants to the offered incentive. In this paper, we only focus on designing an aggregation mechanism among aggregator and consumers.

This problem is formulated as a two-layer controller, as follows:

- A local BTM controller at the consumer level that optimizes battery operation based on the demand, PV generation, retail prices (both time-of-use (ToU) and demand charge) and incentive received from the aggregator. The ultimate goal is to maximize the consumer's profit. Therefore, the controller minimizes the daily operation cost considering the ToU and demand charge, and the profit of trading energy in the wholesale market.
- A controller at the aggregator level that optimizes the incentive offered to each consumer. The outcome will be a daily incentive profile for each consumer which can change from one time instance to another during the day. This way, the aggregator can trade aggregated energy from BTM devices in the wholesale market in order to maximize its own profit. If needed, the proposed structure can adapt a non-profit aggregator model, similar to the market operators at the transmission level.

In the first step, we formulate the problem by assuming that we have perfect prediction of uncertain parameters such as wholesale market price, PV generation, and consumers' load demand. A base-case scenario is designed where the BTM controller only performs ToU and demand charge management, and does not participate in the wholesale

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market. Simulation results from the base-case scenario will be compared with the ones from aggregation scenario to quantify economic benefits for the aggregator and consumers. In the second step, we evaluate the uncertainty of the wholesale market price, PV generation, and load demand on the proposed mechanism, and compare the results with perfect case to reveal the effect of prediction errors.

The rest of the paper is organized as follows. In Section II, we explain the structure of the proposed model, and in Section III, we formulate the optimization problems for the aggregator and consumer layers. Next, in Section IV, we analyze the economic profit of consumers and aggregator under both perfect and imperfect prediction, and finally conclude the paper in Section V.

II. The Proposed Two-Layer Model

Fig. 1 shows the interactions between the retail/wholesale markets, aggregator and consumers in a two-layer structure. There is a two-way communication between the aggregator and consumers, where the aggregator sends a set of possible incentives, $C^i(t)$, to consumer i, and consumer i responds with the amount of power willing to sell to the grid, $Y^i(t)$, for each incentive value $C^i(t)$; i.e. $Y^i(t)$ is a function of $C^i(t)$. Then, the aggregator sell total aggregated energy to the grid at the wholesale market price, $q(t)$. If the aggregator acts as a profitable entity, the incentive offered to the consumers will be a fraction of the predicted wholesale market price; i.e., $C(t) = k.q(t)$ where $0 \leq k \leq 1$. Alternatively, if the aggregator is modeled as a non-profit entity, the incentive signal will be the predicted wholesale market price.

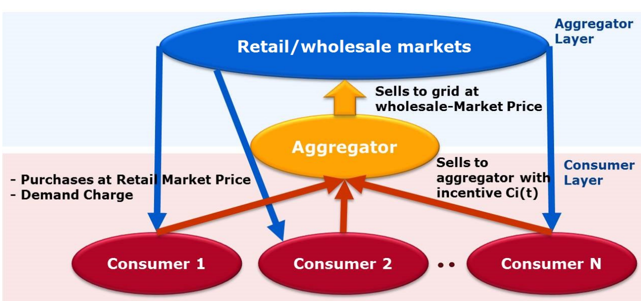


Fig. 1. Conceptual interactions between retail/wholesale markets, aggregator and consumers.

Fig. 2 shows the complex model of the consumer's layer. We assume that every consumer has local PV generation and BTM storage. Consumers purchase power, $X_1(t)$, from utility at the retail market ToU price, $P_0(t)$, and also pays for demand charge. Additionally, all consumers are assumed to participate in the wholesale market via the aggregator, so they are able to sell power back at the incentive price, $C^i(t)$. They can also purchase power, $X_2(t)$, from the wholesale market at price, $q(t)$, which must immediately be stored; i.e., consumer cannot use or sell the power immediately. Moreover, the total amount of power sold to the wholesale market cannot be less than the total amount of power purchased from the same market. This constraint ensures that the consumer does not purchase cheaper energy from the wholesale market for internal use. Please note that consumer is not allowed to sell PV power directly to the wholesale market in the proposed structure.

The ultimate goal of the consumer layer is to find optimum daily charge/discharge profile of the battery, including purchased/sold power from/to the grid, and PV utilization so that the overall operation cost is minimized. Without loss of generality, day-ahead market is chosen as the wholesale market venue for the rest of the paper. It is assumed that the aggregated BTMs satisfies all market requirements.

III. Problem Formulation

A. Aggregator's Layer

We formulate the problem of profit maximization for the aggregator in Eq. 1. Let $C^i(t)$ be the incentive offered to consumer i, and $q(t)$ be the wholesale market price; i.e. the price that aggregator predicts for selling energy back to the grid. In this structure, consumers inform aggregator by the amount of power they will sell/buy to/from the wholesale market for every incentive value $C^i(t)$. Then, aggregator realizes consumers' response denoted as $Y^i(t, C^i(t))$. Therefore, the objective of the aggregator is to find the optimal incentive that maximizes its own profit.

$$\max_{C^i(t)} \sum_{t \in T} \sum_{i \in N} [q(t) - C^i(t)].Y^i(t, C^i(t)) \tag{1a}$$

As explained in Section II, we assume that the incentive is a fraction of the market price; i.e., $C^i(t) = k^i.q(t)$. Thus, Eq. 1 can be simplified to the following form:

$$\max_{k^i} \sum_{t \in T} \sum_{i \in N} [1 - k^i].q(t).Y^i(t, k^i, q(t)) \tag{2a}$$

The value of K^i can be different for each consumer provisioning the physical constraints of the system. This way, lower k^i value can be used for a consumer in a congested area.

Evidently, the response of consumer i is a function of k^i and $q(t)$. In this formulation, we consider the general case where the aggregator makes profit by offering different incentives to consumers. Using this formulation, we can consider three types of aggregators as follows:

- Type I: Aggregator offers different incentives to the consumers while maximizing its own profit;
- Type II: Aggregator offers the same incentive to all consumers while maximizing its own profit;
- Type III: Aggregator offers the wholesale market price to the consumers; i.e. it does not make any profit, and acts similar to an independent system operator.

Later, we will compare the profit of aggregator and consumers under all three types of aggregator's models.

B. Consumer's Layer

In Eq. (3), we formulate the cost minimization problem for consumer i. As it was mentioned earlier, each consumer solves an optimization problem to calculate optimal charge and discharge power of the battery, the amount of purchased/sold energy from/to the grid, and PV utilization for the entire day. In this study, the optimization interval is

15 minutes; i.e $\Delta T = 0.25$ hour. Let $T = \{1, \cdots, T_{max}\}$ be the set of 15-minute time instances during a day; i.e. 96 time instances. Similarly, let T_1 and T_2 be the set of time instances during on-peak periods and partial-peak periods. This is required for any time, on-peak, and partial-peak demand charge calculations.

Also, let variable $X_1^i(t)$ denote the amount of power purchased from the retail market, variable $X_2^i(t)$ denote the amount of power purchased from the wholesale market via the aggregator, and variable $Y^i(t)$ denote the amount of power sold by consumer to the wholesale market via the aggregator. Moreover, let $D^i(t)$ denote the predicted demand of consumer i at time t.

Let $P_0(t)$ be the ToU charge, and P_1, P_2 and P_3 be the cost associated with the maximum purchased power $X_1^i(t)$ at on-peak, partial-peak and entire day, respectively. Moreover, let $q(t)$ be the predicted wholesale market price and $C^i(t)$ be the incentive price offered by the aggregator.

Let $PV^i(t)$ be the variable denoting the amount of solar power utilized by consumer i, and $PV_{max}^i(t)$ be the maximum available power from PV at time t for consumer i.

Let variable $R^i(t)$ be the power of battery, where $R^i(t) > 0$ when it is charging and $R^i(t) < 0$ when it is discharging. In addition, let R_{max}^i be the maximum charging or discharging power of the battery. Finally, let $S^i(t)$ be the amount of stored energy, and let S_{max}^i be the maximum capacity of the energy storage.

$$\min \sum_{t\in T}[P_0(t).X_1^i(t) + q(t).X_2^i(t) - C^i(t).Y^i(t)] + P_1.\max_{t\in T_1} X_1^i(t) + P_2.\max_{t\in T_2} X_1^i(t) + P_3.\max_{t\in T} X_1^i(t) \tag{3a}$$

$$s.t \quad X_1^i(t) + PV^i(t) - Y^i(t) - R^i(t) = D^i(t) \qquad t \in T \tag{3b}$$

$$\sum_{t\in T} X_2^i(t) \le \sum_{t\in T} Y^i(t) \tag{3c}$$

$$0 \le PV^i(t) \le PV_{max}^i(t) \qquad t \in T \tag{3d}$$

$$0 \le X_1^i(t), X_2^i(t), Y^i(t) \qquad t \in T \tag{3e}$$

$$X_2^i(t).Y^i(t) = 0 \qquad t \in T \tag{3f}$$

$$X_2^i(t).R^i(t) \ge 0 \qquad t \in T \tag{3g}$$

$$S^i(t+1) = S^i(t) + (R^i(t) + X_2^i(t)).\Delta t \qquad t \in T - T_{max} \tag{3h}$$

$$|R^i(t) + X_2^i(t)| \le R_{max}^i \qquad t \in T \tag{3i}$$

$$S_{min}^i \le S^i(t+1) \le S_{max}^i \quad t \in T - T_{max} \tag{3j}$$

$$S^i(1) = S_{min}^i \tag{3k}$$

$$S^i(T) + (R^i(T) + X_2^i(T)).\Delta t = S_{min}^i \tag{3l}$$

The objective of consumer i is to minimize its energy cost which is equal to the cost of purchased energy from retail market plus the demand charge minus the benefit obtained by trading energy in the wholesale market as denoted in eq. (3a). Constraint (3b) guarantees that supply and demand balance is maintained at every time slot t, and constraint (3c) ensures that the total amount of sold power to the wholesale market is greater than or equal to the total amount of power purchased from the same market. Moreover, constraints (3d) and (3e) enforce the upper and lower bounds on the variables. Constraint (3f) prevents consumers from purchasing and selling energy simultaneously. Constraint (3g) requires consumers to store purchased energy from the wholesale market immediately: i.e., battery cannot be discharged during this time; if $X_2^i(t) > 0$, then $R^i(t) \ge 0$. Equation (3h) calculates the battery state-of-charge (SOC) level at the beginning of the next iteration with respect to the charge/discharge power of current step, and constraints (3i) and (3j) enforce upper and lower bounds on the battery power and SOC. Finally, constraints (3k) and (3l) ensure that battery starts and ends with the same amount of energy, assumed to be S_{min}^i in this paper, which guarantees energy neutrality at the end of the day.

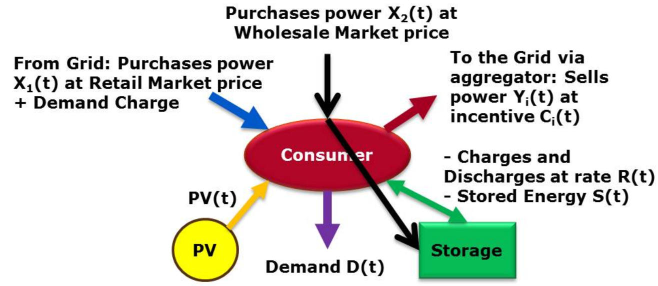


Fig. 2. Consumer Layer and its interaction with aggregator and retail market.

It can be seen that the objective function (3a) as well as constraints (3f) and (3g) are non-linear. These equations can be linearized by introducing new slack variables; however, due to space limitation, we do not explain the details here.

IV. Simulation Studies and Analysis

As it was mentioned earlier, analyses are carried out for participation in the day-ahead energy market. We would like to find the optimal incentive offered by aggregator to each consumer, the amount of power that consumer will sell to the grid, and the daily charge/discharge profile of the battery. When these parameters are determined by solving the optimization problem at each layer, we will be able to quantify the revenue of aggregator as well as the net profit of the consumer. The profit for consumer is the total saving obtained by utilizing battery after deducting the average daily cost of storage, which is the total cost of storage $(1100 \times R_{max}^i + 300 \times S_{max}^i)$ divided by the number of useful cycles in service (assumed to be 6000 cycles). The number of cycles per day is calculated by $\frac{\Delta T}{2S_{max}^i} \times \sum_{t\in T} |R^i(t)|$.

A. Base-case Scenario

In the base-case scenario, each consumer utilizes the storage locally to minimize ToU cost and demand charge; i.e. no aggregator is involved and the consumer does not trade energy in the wholesale market. In this case, problem formulation is a subset of those introduced in Section III-B, and the objective is to minimize the local energy consumption which consists of the ToU cost as well as the demand charge. Note that comparing the profit of consumer with and without aggregation quantifies the economic benefit of the aggregation control mechanism.

B. Data

The following data are required to analyze the behavior of consumers and aggregator.

- ToU price and Demand Charge [14]: P_0, P_1, P_2, P_3
- Physical constraint of the storage belong to consumer i: S^i_{max}, R^i_{max}
- Day-ahead energy price prediction [15]: $q(t)$
- Load demand prediction for consumer i [16]: $D^i(t)$
- PV generation prediction for consumer i: $PV^i_{max}(t)$

In this study, aggregation of six different loads are considered. Simulation studies are performed for the 1^{st} and 15^{th} day of every month in a year, i.e., 24 days in total.

C. Perfect Prediction Scenario

In this scenario, we analyze the control mechanism under the assumption of prefect prediction; i.e. there is no error in the predicted values. This scenario, although unrealistic, quantifies maximum achievable benefits for aggregator and each consumer by participating in the wholesale market through the proposed two-layer aggregation mechanism and set a legitimate base for comparison.

1) Consumers' and Aggregator's Profit: Fig. 3 shows monthly profit of type I aggregator in a year. The average daily profit of the aggregator per consumer is \$28 which results in \$10220 annual profit per consumer for the aggregator.

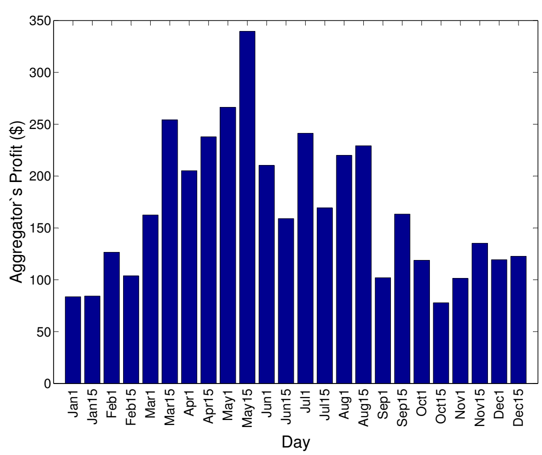


Fig. 3. Monthly profit of Type I Aggregator

Fig. 4 shows the average daily profit of consumers under Type I aggregation. It can be seen that for all consumers, the net profit increases under aggregation compared to base-case (local) scenario. Note that the percentage values indicate extra net profit gained by consumers via aggregation.

Table I compares the profit of consumers and aggregator under different types of aggregation in more details. The simulation results indicate that the consumers' cost decreases more under type III aggregator compared to type II aggregator. However, in some cases the average daily cost of the storage has increased which caused smaller net profit for consumers under type III aggregation.

2) Behavior of Consumer in a Day: Fig. 5 reveals a consumer behavior in a day. It distinctively shows when the consumer purchases/sells power from/to the grid, as

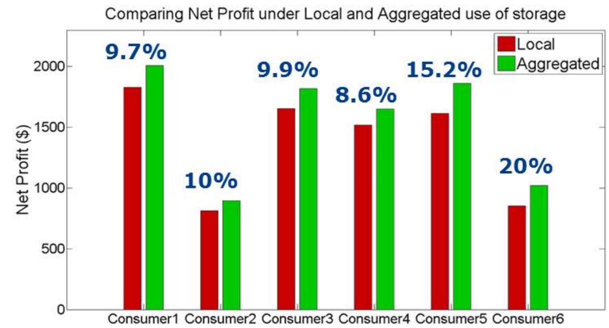


Fig. 4. Net Profit of Consumers under Type I aggregation

well as charging and discharging of storage. Typically, it is economical to sell power in the wholesale market at the end of the day. The reason is that the consumer uses the purchased power from the wholesale market during high retail market prices (ToU) and sells back excess power to the wholesale market later at night when local load consumption is low. Remember that each consumer will sell energy to the wholesale market equal or more than the total purchased energy from the same market. So consumer will not be able to exploit the wholesale market in this framework.

D. Imperfect Prediction Scenario

In this Section, we introduce a realistic scenario where imperfect prediction of the day-ahead wholesale market price $q(t)$, consumer load demand $D^i(t)$ and PV generation $PV^i_{max}(t)$ are available. We use the average of five previous days $Avg\text{-}q(t)$, $Avg\text{-}D^i(t)$ and $Avg\text{-}PV_{max}(t)$ as a simple prediction model in this study.

The predicted values are used in the day-ahead wholesale market where the aggregator commits to pay the incentive $C^i(t)$ and consumer i promises to sell power at $Y^i_{exp}(t)$. However, in real-time during the next day, consumer's controller operates under the actual day-ahead market price $q(t)$, known from day-ahead market operation, and has a better prediction for $D^i(t)$ and $PV^i(t)$. Thus, the consumer might prefer to sell less power to the grid and be penalized in order to increases its own profit. To evaluate this sort of conditions, we perform a real-time analysis by solving the optimization problem every 15 minutes (with actual day-ahead wholesale market prices and better prediction of $D^i(t)$ and $PV^i(t)$) to find the actual power sold to the aggregator and consequently, the actual profit of aggregator and consumers. We assume that in the real-time operation, consumer cannot sell more than the committed power $Y^i_{exp}(t)$; however, if it sells less than the committed power, it will be penalized at the wholesale market price; i.e. it should pay $q(t).[Y^i_{exp}(t) - Y^i(t)]$ to the grid. Again, the total purchased energy from the wholesale market is enforced to be equal or less than the energy sold to the wholesale market by the end of the day.

Moreover, we assume that in the real-time operation, consumer has better prediction of load demand and PV generation, as it moves towards the end of the day. Let $AvgData(t)$ be the average of the data from 5 previous days, and $RealData(t)$ be the real data at time t of the same day. At any time t_0 of the day, the error of predicted data for time $t > t_0$ is as follows: $error(t) = \frac{t-t_0}{24} \times [AvgData(t) -$

TABLE I
AGGREGATOR: AVERAGE DAILY PROFIT PER CONSUMER; CONSUMER: AVERAGE DAILY NET PROFIT IN DOLLARS AND THE EXTRA NET PROFIT PERCENTAGE

	Daily Profit ($) – Extra Net Profit(%)		
	Type I	Type II	Type III
Aggregator	$28	$23.5	$0
Consumer1	$177 – 9.7%	$177 – 9.7%	$204 – 11.1%
Consumer2	$82 – 10.0%	$113 – 13.9%	$90 – 11.0%
Consumer3	$164 – 9.9%	$173 – 10.4%	$187 – 11.3%
Consumer4	$131 – 8.6%	$164 – 10.8%	$148 – 9.8%
Consumer5	$246 – 15.2%	$240 – 14.8%	$297 – 18.4%
Consumer6	$170 – 20.0%	$177 – 20.8%	$170 – 19.9%

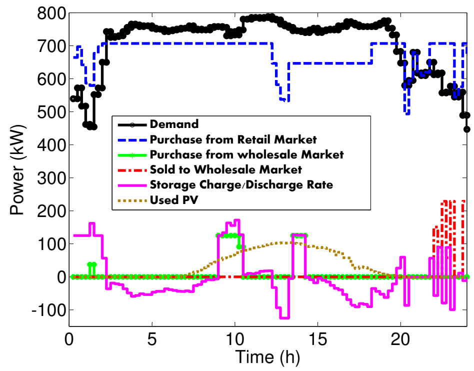


Fig. 5. Behavior of a consumer during a day (July 01)

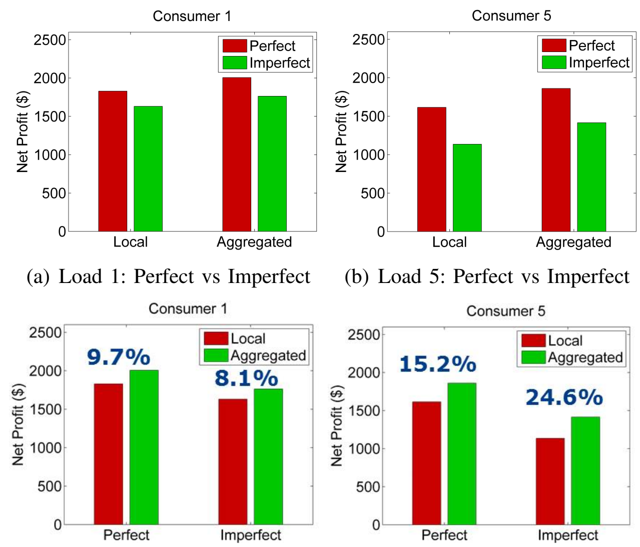
$RealData(t)]$ where t and t_0 are time instances in hour. We use $RealData(t) + error(t)$ as the new predicted values.

Figs. 6(a) and 6(b) indicate that for both consumers, the net profit decreases under imperfect prediction scenario for a year of simulation. Additionally, Figs. 6(c) and 6(d) show that for both consumers, participation in the aggregation program is still more profitable than the only local use of storage under the imperfect prediction. While extra net profit for consumer 1 is decreased from 9.7% to 8.1% in imperfect case, net profit for consumer 5 has increased from 15.2% to 24.6%. Finally, the simulation results indicate that the average daily profit of the aggregator per consumer is $18 which results in $6570 annual profit per consumer; i.e., about 36% reduction in profit because of imperfect knowledge. In all simulation results, the annual net profit for every consumer was increased even in the case of imperfect scenarios. Thus, by improving the prediction method, the profit potentially can be increased.

V. CONCLUSION

In this paper, we designed a two-layer incentive-based controller for aggregation of BTM storage devices. We considered the participation of storages in the day-ahead energy market under both perfect and imperfect prediction scenarios, and calculated the aggregator and consumers' profits.

Different simulation for 24 days of a year and six consumers showed that aggregation creates about 12% extra revenue stream for every consumer on average considering the wearing cost of the storage. Also, the proposed model offers scalable and local decision-making framework, following the TE principles. Furthermore, it is fully automated on the consumers' side which facilitates their participation in the aggregation program.



(a) Load 1: Perfect vs Imperfect (b) Load 5: Perfect vs Imperfect
(c) Load 1: Local vs Aggregated (d) Load 5: Local vs Aggregated

Fig. 6. Comparing Profit under perfect and imperfect scenarios

REFERENCES

[1] J. Neubauer and M. Simpson, "Deployment of behind-the-meter energy storage for demand charge reduction," *Golden, CO*, 2015.

[2] M. P. Johnson, A. Bar-Noy, O. Liu, and Y. Feng, "Energy peak shaving with local storage," *Sustainable Computing: Informatics and Systems*, vol. 1, no. 3, pp. 177–188, 2011.

[3] A. Mishra, D. Irwin, P. Shenoy, and T. Zhu, "Scaling distributed energy storage for grid peak reduction," in *Proceedings of the fourth international conference on Future energy systems*. ACM, 2013, pp. 3–14.

[4] A. Purvins, I. T. Papaioannou, and L. Debarberis, "Application of battery-based storage systems in household-demand smoothening in electricity-distribution grids," *Energy Conversion and Management*, vol. 65, pp. 272–284, 2013.

[5] P. M. van de Ven, N. Hegde, L. Massoulié, and T. Salonidis, "Optimal control of end-user energy storage," *IEEE Transactions on Smart Grid*, vol. 4, no. 2, pp. 789–797, 2013.

[6] R. Sharma, B. Asghari, and S. A. P. Kani, "Method for real-time power management of a grid-tied microgrid to extend storage lifetime and reduce cost of energy," Apr. 28 2015, uS Patent 9,020,649.

[7] K. Worthmann, C. M. Kellett, P. Braun, L. Grüne, and S. R. Weller, "Distributed and decentralized control of residential energy systems incorporating battery storage," *IEEE Transactions on Smart Grid*, vol. 6, no. 4, pp. 1914–1923, 2015.

[8] P. Braun, L. Grüne, C. M. Kellett, S. R. Weller, and K. Worthmann, "A real-time pricing scheme for residential energy systems using a market maker," in *Control Conference (AUCC), 2015 5th Australian*. IEEE, 2015, pp. 259–262.

[9] P. Braun, C. M. Kellett, S. R. Weller, K. Worthmann *et al.*, "Predictive control of a smart grid: A distributed optimization algorithm with centralized performance properties," in *2015 54th IEEE Conference on Decision and Control (CDC)*. IEEE, 2015, pp. 5593–5598.

[10] Y.-J. Kim and L. K. Norford, "Price-based demand response of energy storage resources in commercial building," in *2016 IEEE Power and Energy Society General Meeting*. IEEE, 2016.

[11] D. D. Sharma, S. Singh, and J. Lin, "Multi-agent based distributed control of distributed energy storages using load data," *Journal of Energy Storage*, vol. 5, pp. 134–145, 2016.

[12] K. Subbarao, J. C. Fuller, K. Kalsi, A. Somani, R. G. Pratt, S. E. Widergren, and D. P. Chassin, "Transactive control and coordination of distributed assets for ancillary services," *Pacific Northwest National Laboratory, Richland*, 2013.

[13] K. Kok and S. Widergren, "A society of devices: Integrating intelligent distributed resources with transactive energy," *IEEE Power and Energy Magazine*, vol. 14, no. 3, pp. 34–45, 2016.

[14] [Online]. Available: http://www.pge.com/tariffs/tm2/pdf/ELEC_SCHEDS_E-19.pdf

[15] [Online]. Available: http://www.energyonline.com/Data

[16] [Online]. Available: https://open-enernoc-data.s3.amazonaws.com/anon/meta/index.html