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Agent-Based Energy Consumption Scheduling for Smart Grids: An Auction-Theoretic Approach

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ABSTRACT The future smart grid would help to benefit both the users and the electricity providing companies from smart pricing techniques. In addition, smart pricing can be used to achieve social objectives and would in turn fluctuate wholesale market into demand side. Collecting abundant information regarding the users electricity consumption pattern is a challenging task for utility providing companies. That is, users may not be willing to expose their indigenous information without any incentive. In this paper an Optimal Energy Consumption Scheduling (OECS) mechanism is proposed to tackle this problem. An agent-based forecasting method is designed, which is capable of predicting energy consumption of each consumer with a lead-time of one hour. This forecasting is exploited to estimate the cost of buying required amount of energy from multiple suppliers. Consequently, based on the estimated required energy and cost, an auction mechanism is proposed to optimize the energy traded between consumers and multiple suppliers within a smart grid. The objectives include increased efficiency and cost reduction of electricity usage by the end users. The results and properties of the proposed OECS mechanism are studied, and it is shown that the auction technique is budget balanced for distribution of electrical energy among consumers from diverse renewable generation resources. Extensive numerical simulations are also conducted to show and prove the beneficial properties of OECS mechanism.

INDEX TERMS Smart grid, energy load prediction, demand response, energy consumption scheduling, energy management, Vickrey-Clarke-Groves mechanism, social choice function, Nash equilibrium.

I. INTRODUCTION

A smart grid is an electrical network that allows bi-directional flow of electricity and information exchange between suppliers and consumers [1]. This system has potential to increase power system reliability, reduce network losses, and encourage consumers' participation in energy management [2]. Smart grid technology facilitates the consumers to analyze their electricity utilization information in real time, this enables them to manage electricity bills by scheduling consumption to off-peak hours [3]. Technology like intelligent sensors, data management system and two-way communication in smart grid are responsible for such benefits. Increasing use of electricity made it difficult for utility companies to reliably and efficiently fulfill the demand of their consumers [4]. Average utilization of generation capacity is recorded below 55% in off-peak hours [5]. Therefore, designing a grid to fulfill only peak demand of electricity is not feasible [6]. It triggered the research towards Demand Side Management (DSM), which focuses not only on electricity load shifting but also on reducing consumption. Smart pricing is a vital characteristic of DSM that encourages users to utilize electricity efficiently which in tern benefits both the supplier and consumers [7]–[11].

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DSM requires either full or partial information of users' electricity consumption patterns, and sometimes users are not willing to reveal their personal information. Users may also alter their electricity consumption patterns based on real-time pricing, unaware that this amount of load shifting may increase the value of real-time pricing [12]. This load shifting can convert off-peak times into peak times, making it very difficult for a supplier to cater the demand [13], [14]. Therefore, above- mentioned assumption is not a fruitful approach [15], [16]. An auction-based mechanism where bidders send their bids to be evaluated by a third party agent could be a solution to this issue. Under this construct, the demands of higher bidders are fulfilled to maintain reliability of an electric grid, even in the peak hours [17].

In recent years, significant research has been conducted on demand side management, which focused on scheduling user demand according to real-time pricing [18]. In particular, Samadi proposed an auctioning scheme based on efficient pricing algorithm using Vickrey-Clarke-Groves (VCG). VCG based mechanism is used to maximize social benefits of each user [19], [20]. To calculate payments, energy providers require accurate information of users' energy demands and constraints [21]. Systems are therefore designed to calculate incentive for users based on their truthful declaration of information. The benefits to users are modeled as utility functions [22].

Mohsenian-Rad *et al.* proposed an energy consumption scheduling game based on cooperative game theory, where each consumer acts as a player and scheduling of daily household load are their strategies [23]–[26]. Optimal performance in terms of minimizing energy costs is achieved via Nash Equilibrium for the proposed energy consumption scheduling game. To ensure users' participation, incentives are also calculated. Similarly Salinas *et al.* presented a third-party tool for managing the energy consumption of a group of users [27], [28]. Users are bound to shift their load to off-peak hours to minimize their utility bills, which will ultimately lead to increased grid generation utilization, even during off-peak hours [28].

Load scheduling problems are formulated as a constrained multi-objective optimization problem (CMOP) [29], [30]. The optimization objectives achieved through CMOP mechanism includes minimize the electricity consumption cost and maximize utility. Two Evolutionary Algorithms (EAs) are designed to obtain the Pareto front solutions and ϵ-Pareto front solutions for the multi-objective optimization problem. Different residential load controlling techniques have been compared by Rasheed *et al.* [18], Khalid *et al.* [7], Javaid *et al.* [5], and Afzal *et al.* [3].

Multiple mechanism designs are available to solve the problem of cost optimization and reduce peak-to-average ratio (PAR). Literature studies indicated that VCG was most efficient and well-known mechanism due to its accuracy [31]. It is very important that an applied mechanism is able to accurately reveal users' information, and VCG performs best in this respect. Energy consumption controller for demand side management in smart grid using VCG mechanism is proposed in [20], [32]. The objective was to change users' total energy consumption by shifting load to off-peak hours but this mechanism was not budget balanced. Although efficiency and truthfulness of user's information in VCG was tested but budget imbalance of the designed mechanism was not validated [33].

Moreover, Vickrey-Clarke-Groves mechanism inherently encounters the budget imbalance in public goods problem [34]. Therefore, any deficit towards consumers or suppliers will effectively limit their further participation. This budget imbalance is dependent upon the profile types of consumers [3], [20], [35].

In VCG user's payments are not exactly equal to their submitted bids, it depends on the profile valuation of all other participants [36]. Furthermore, to overcome the stated issue of VCG mechanism, another mechanism named "Moulin Mechanism" is implemented in this research, which will calculate a surplus represented as rebate given to consumers, which will in turn help to reduce budget imbalance problem. The rebate of consumers depends upon the type profile of all other participants. Thus rebate is not destroying the structure of the VCG payments, ensuring that allocative efficiency and Dominant Strategy Incentive Compatible (DSIC) properties are retained. This research will interchangeably use the word Smart Home User (SHU), consumer and buyer.

Furthermore, using existing mechanism [34] for p items, bidders must submit sufficient information to determine $2^p - 1$ bids for all combinations of p items. This exponential growth of the process increases the number of items, it significantly increases the bid preparation time. This mechanism increases the total simulation time of the system with increased number of participants, which ultimately reduces overall efficiency of the mechanism [16].

Above discussion triggers the need of a mechanism that is budget balanced and efficient in term of bid allocation. This research is an extension of our previous work [37], that presented an algorithm for an agent based energy load prediction using weighted average prediction approach. This research aims to predict cost of Predicted Load (PL). The idea is to broadcast PL information of each Smart Home User (SHU) using multi-agent system. It also aims to calculate cost to get PL from multiple resources including in-house generation, neighboring smart homes and other electricity providers interested in trading of electricity. Payoff of each SHU to measure benefit of using the OECS mechanism is calculated. Utility companies should have knowledge of user preferences to achieve maximum consumer social benefits [16].

A game-theoretic auction based mechanism is proposed in this research, in which electricity consumers are players of the game and their valuation profiles against each supplier are strategies. Players' bids are sent to a third party Control Agent (CA). The CA evaluates all bids and negotiates with multiple suppliers to fulfill the demands of players based on their valuation profile. The system then determines the payment amounts for each player based on the profiles of other payers to maximize social benefits for all players. By implementing OECS both grid reliability and budget balance are maintained, even in peak hours. Optimal performance in terms of increase in payoff function of each player is achieved via the Nash Equilibrium of the OECS mechanism.

A mixture of distributed and centralized approach is proposed. Buyer considers maximum benefit from chosen resources of electricity. At distribution level, buyer first fulfills energy consumption requirement from in-house generation, which is the cheapest resource of electricity. Then, centralized approach is used where every SHU's prefer to buy electricity from neighboring SHU's, which is also cheapest due to closest resource as energy transmission

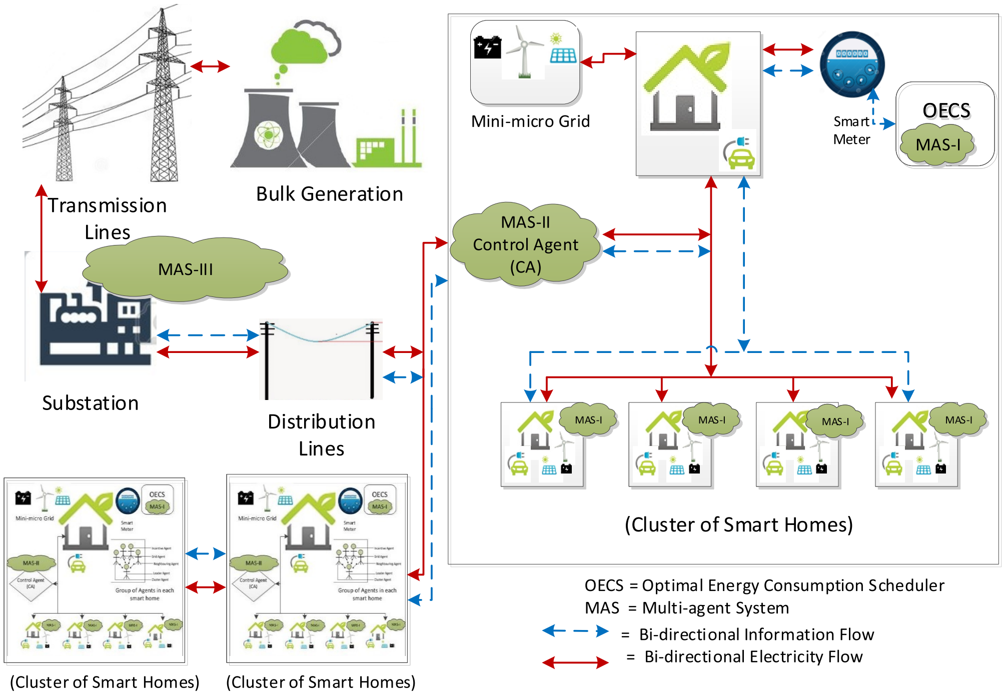

FIGURE 1. Proposed system model with multi-agent system at both production and consumption level.

cost is also considered in OECS. To fulfill further demand each SHU's consider electricity trading using coordination between multi-agent systems. Every SHU can participate in trading. At the end, total electricity bill is calculated which depends how much quantity is selected from each resource. After systematically analyzing literature, it was found that agent based electricity trading requires more researchers' attention, more research is required towards semi-centralized and multiple consideration approaches. Moreover, positive and negative surplus for each SHU is also calculated in the form of rebate to make the mechanism budget balanced. Tentative electricity bill is also shown to electricity buyer's one-hour prior to actual usage time interval.

The contribution of this work is summarized as follows:

- An agent-based forecasting method is designed, which is capable of forecasting the amount of energy consumed by each consumer with a lead time of one hour.
- The forecasted information is exploited to estimate cost of buying required energy from multiple suppliers.
- Based on the information of estimated energy and cost, OECS mechanism is implemented to optimize energy traded between consumers and multiple suppliers.

The remainder of the paper is organized as follows. In section II, a detailed description of the proposed system model and the role of a multi-agent system in a residential load control scheme are presented. The game-based auctioning mechanism for optimal energy consumption scheduling on a smart grid is explained in section III. In section IV, performance of the proposed auctioning scheme is evaluated based on simulation parameters. Finally, our concluding remarks and future directions are stated in section V.

II. SYSTEM MODEL

In this section, an agent-based Optimal Energy Consumption Scheduling (OECS) model is proposed. To implement the proposed system model, some infrastructure changes are required at both consumption and distribution levels. A smart community comprising of a large number of smart homes is considered. A residential area is divided into multiple clusters, each cluster presents 3-4 smart homes. Every smart home is equipped with distributed energy generation and storage units (shown in Fig. 1). SHU's are the sellers as well as buyers of electricity within a community.

At initial stage to train agents, Andersen model [38], [39] is used which performs load aggregation technique. Aggregated load of SHU is calculated based on the category of user. Other categorical variables used in calculating aggregated load are, hours of the day, types of days (weekday and weekends), and months. Moreover, the weather changes according to months therefore daily profile of every SHU may change according to the month of the year. With hourly metering of individual customers using Advanced Metering Infrastructure (AMI), data for individual consumption profiles is taken from [40]. The proposed system consists of multiple steps as explained below:

Step 1: Each MAS-I, shown in Fig.1, computes the PL of each SHU to which they belongs. The predicted load (PL^j_{t+1}) of a smart home user j, for upcoming time slot $t+1$ is calculated as follows.

$$PL^j_{t+1} = \{f^j_{1,t+1} * w_{1,t} + f^j_{2,t+1} * w_{2,t} + f^j_{3,t+1} * w_{3,t} + \dots + f^j_{m,t+1} * w_{m,t}\}/m \quad (1)$$

PL^{j}_{t+1} is based on two factors, agents i advice ($f^{j}_{i,t+1}$) and weight of agent ($w_{i,t}$). Predicted load is calculated by taking mean value of above-mentioned factors. Advice $f^{j}_{i,t+1}$ of single agent i belongs to set F of an expert agent's advice, i.e., $F = f^{j}_{1,t+1}, f^{j}_{2,t+1}, f^{j}_{3,t+1} \ldots\ldots.., f^{j}_{m-1,t+1}, f^{j}_{m,t+1}$. Set of advice is maintained by taking data with some variations from SHU's previous electricity consumption pattern. m is the total number of agents and $w_{i,t}$ belongs to set W of expert's weights. Weights are in a range of 1-5 used as scaling factor. More detail of these values are explained in section IV.

Step 2: Based on step 1 calculation, MAS-I calculates the cost to get electricity from in-house mini micro-grid that is explained in detail in section III. Furthermore, in case of system failure each smart home user can utilize their mini micro-grid generation and storage unit [41], [42]. User can also get electricity from grid via grid connection shown in Fig. 1.

Step 3: To fulfill further demand, MAS-II will calculate cost to get electricity from neighboring SHU's (SHU can sell their surplus electricity). Selling surplus electricity is one of the core objectives of this research, explained in section III.

Step 4: Until PL is still not fulfilled, system has two options, first, play game with multiple suppliers (including other smart homes, other electricity supplier companies or a grid itself) by submitting valuations against remaining PL and second, get electricity directly from grid using current tariff (which may be very high in peak hours). The electricity rates of grid will increase, when all the demands are shifted towards grid. Moreover, it is in favor of SHU to fulfill remaining PL by participating in the game.

Step 5: Buyers submit energy valuation vector against PL. Buyer can submit multiple offers using OECS mechanism.

Step 6: Winner players will get their required electricity at the cheapest rate.

Step 7: Looser player can either switch electricity demand or use grid electricity supplier to fulfill remaining PL.

Step 8: The estimated total electricity bill of every buyer j_b to buy PL for time slot t is calculated, one hour earlier explained in section IV. The variation in bill may occur depending on the change in electricity usage pattern. Users can compare their electricity bills with and without using the system.

Step 9: When actual time t is revealed, weights of expert agent's are revised based on the accuracy of the prediction. Algorithm 1 is used for re-assignment of agents' weights [37]. According to the algorithm, for every user j, actual load (AL^{j}_{t+1}) is compared with each agent's advice ($f_{i,t+1}$), if the difference is within defined threshold then weight of that agent for next time slot is increased otherwise decreased.

III. OPTIMAL ENERGY CONSUMPTION SCHEDULER

A. PROBLEM FORMULATION

Every buyer j_b submits valuation against PL of electricity to sellers. Payment function $P_j(.)$ for buyer is calculated associated with quantity of electricity demanded. This payment is in cents per kilowatt hour at which a seller j_s is

Algorithm 1 Weight Re-Assignment Algorithm

Input: Set of agents (A), agents' advise (F), agents' weights (W), total number of agents (m), actual load AL^{j}_{t+1} of user j for time $t+1$. Dataset (D), total number of users (n) **Output:** Updated weights (W). At start to initialize advice F, all agents get data from D [40] (previous actual load available according to day, time and month).
Initialize user j = 1.
Initialize agent i = 1.
while ($j <= n$) **do**
  Define threshold S for t.
  repeat
    if $|AL^{j}_{t+1} - f_{i,t+1}| <= S$ **then**
      $w_{i,t+1} = w_{i,t} + 1$
    else
      $w_{i,t+1} = w_{i,t} - 1$
    end if
    Increment i.
  until ($i <= m$)
  Increment j.
end while

ready to sell quantity q of the electricity. Resources follow a quantity–price strategy, formed as a pair of quantity and price, expressed as (q_{j_s}, p_{j_b}). To balance the load between sellers and buyers of the electricity, an increasing convex price function is adopted to calculate the price payed by buyer j_b against the quantity q of predicted load (PL). The cost function can be defined as:

$$P_{j_b}(q) = q_{j_s} \times c_{j_s} \tag{2}$$

Subject to

$$P_{j_b}(q) = \begin{cases} c_{j_s} \geq 0 & \text{for } q \leq q_{j_s} \\ +\propto & \text{for } q > q_{j_s} \end{cases}$$

The cost function in Eq. (2) indicates that price $P_{j_b}(q)$ payed by buyer j_b depends on the quantity q_{j_s} and q_{j_s} is the maximum quantity of electricity that seller j_s can provide. c_{j_s} is the per unit electricity cost imposed by seller j_s. Constraints shows that; for higher quantities, the cost becomes infinite. The multi-agent system selects the quantity $\overline{q}$ to purchase from each seller j_s. Assuming the the demand is completely satisfied at the scheduled price. It can be expressed as:

$$\sum_{j_s=1}^{s'} \overline{q_{j_s}} = d_{j_b} \tag{3a}$$

Constraints:

$$\overline{q_{j_s}} \geq 0 \tag{3b}$$

$$(\overline{q_{j_s}}) \leq q_{j_s} \tag{3c}$$

where d_{j_b} is the total demand of buyer j_b and $\overline{q_{j_s}}$ is the amount of electricity provided by seller j_s. Eq. (3a) indicates that the amount of electricity collected from multiple suppliers of electricity is equal to the demand of buyer j_b. s' is the total number of suppliers. Constraints (3b), (3c) ensure that amount of electricity purchased should not be zero and quantity ($\overline{q_{j_s}}$) of electricity purchased from the seller j_s should not be greater than the available quantity (q_{j_s}) at the seller site. The objective is to minimize the total system cost. The electricity bill of every buyer j is calculated depending on the amount of electricity and per unit price defined by seller. The objective of this model is to minimize the electricity cost for SHU. The objective function can be written as

$$\min \sum_{j_b=1}^{n} Bill_{j_b} \tag{4a}$$

In other words:

$$\min \textstyle\sum_{j_b=1}^{n} P_{j_b} \tag{4b}$$

$$s.t. \textstyle\sum_{j_b=1}^{n} \sum_{j_s=1}^{s'} (c_{j_s} \times \overline{q_{j_s}})_{j_b} \tag{4c}$$

$$P_{j_b} = C_h^{j_b} + C_n^{j_b} + P_g^{j_b} \tag{4d}$$

Eq. (4b) indicates that the objective is to minimize the electricity cost for all buyers. Eq. (4c) is derived by substituting the value of P_{j_b} in Eq. (4b) from Eq. (2). For single buyer j_b price can be written as Eq. (4d). In Eq. (4d), $C_h^{j_b}$ is the cost to fulfill electricity demand of SHU from in-house generation. $C_n^{j_b}$ is the cost to get electricity from neighboring smart home seller. The detail of these two parameters has been published by the author of this research work in [43]. OECS game is performed with $P_g^{j_b}$ (payment paid by buyer j_b to get the electricity from grid).

B. AUCTIONING IN SMART GRIDS TO MINIMIZE COST

The objective function described in the previous section is a merger of centralized and distributed management performed by multi-agent system. The cost to fulfill demand of electricity from in-house generation is calculated at distributed level, similarly cost to fulfill further demand from neighboring smart homes is also calculated at cluster level. In case if demand is not satisfied then all the requests are transferred to electricity supplier company. In this scenario (which is most common), the demands of those electricity buyers are guaranteed who are willing to pay more than other buyers. To make sure that system remains budget balanced and no participant will end up with negative payment, the system is controlled at centralized level. Negative payment means participants are suffering with loss as compared to others, which stop them from further participation.

For example, n consumers demand d identical objects and $d < n$; obviously all demands cannot be fulfilled to make system stable. Identical objects (d) will be assigned to those consumers (n) who value the objects more than other consumers, so that $d = n$. To achieve this objective in smart grid, a game-based auctioning mechanism is proposed, to make the electricity grid reliable even in insufficient electricity conditions.

C. ENERGY TRADING GAME MODEL

The proposed energy trading game requires participation from all players. Every SHU, whose electricity demand is not fulfilled at local level (from in-house generation and neighboring smart homes seller) is the player of the game.

Multi-agent system at residential level plays this game based on their SHU's preferences. Preferences include the flexibility of their shiftable loads. Every smart home user can be winner as well as loser of the game. In case, if smart home user becomes a loser of the game, he will shift his flexible load to other time slots or use grid Time of Use (TOU) tariff. In this research work, details of load type of every SHU are not considered. It is assumed that SHU's set valuations according to the preferences of loads against time of the day. Electricity need of every user is different from each other according to their electricity consumption pattern therefore any player can not determine the valuations of other players until they are not declared openly.

Each buyer player j_b has an energy valuation vector $E(j_b)$ for trading the electricity, $E(j_b) = [q_{v^1_{jb}}, q_{v^2_{jb}}, \ldots]$. $q_{v_{jb}}$ indicates the quantity of electricity (q) that buyer j_b wants to buy, at the valuation of v_{j_b}. Valuation is cost that buyer j_b is willing to pay against the defined quantity. Similarly every buyer j_b maintain his energy valuation vector based on his valuation. Energy valuation vector give more freedom to the buyers and increase their chances to win the game. For instance, each buyer submits multiple quantities vs. valuation in energy valuation vector (the price SMU is willing to pay against the defined quantity) to increase the chances of winning the game. Therefore, if buyer is becoming a looser in a system using valuation $q_{v^1_{jb}}$, then he can be a winner using second valuation $q_{v^2_{jb}}$, depending on the quantity of surplus energy at seller site. s.t

$$q_{v^2_{jb}} > q_{v^1_{jb}} \tag{5}$$

The ultimate goal of each buyer is to select the lowest energy valuation vector that minimize the cost but it should not be very less so that the chances of winning game becomes low. In short, each buyer wants to select the valuation that reduces electricity bills. In this mechanism design, the outcome is represented as a vector $x = (y_1, y_2, \ldots, y_n, p_1, p_2, \ldots, p_n)$

$$y_j = \begin{cases} 1 & \text{if buyer } j_b \text{ receive the object} \\ 0 & \text{otherwise} \end{cases}$$

where, p_j is the payment transferred through buyer j_b.

$$x = (y_1, \ldots, y_n, p_1, \ldots, p_n), \; y_j \in \{0, 1\}, \; p_j \in R,$$
$$\forall j \sum_{j=1}^{n} y_j = 1, \sum_{j=0}^{n} p_j \leq 0 \tag{6}$$

First, the system will play game by getting first valuation from energy trading vector of every buyer j_b. The valuation of each agent is its private information and must be revealed truthfully to ensure incentive compatibility in the system;

however, valuation should always be positive $v_{j_b} \geq 0$. The profile of valuation $V = [v_{j_b}, v_{(j_b+1)}, v_{(j_b+2)}, \ldots, v_z]$ is maintained by getting all the valuations from all buyers. v_{j_b} is the valuation submitted by first player j_b and $v_{(j_b+1)}$ is the valuation submitted by second buyer and so on. z is the total number of buyer participating in the game. The permutation of valuation v^* where, coordinates are arranged in decreasing order is calculated to find the highest valuators.

$$v^{*1} \geq v^{*2} \geq \ldots.. \geq v^{*z} \tag{7}$$

For buyer agent j_b, the valuation the profile V_{-j_b} is obtained by eliminating j_b^{th} coordinate from profile of valuation (V). Similarly v^*_{-jb} denote the permutation after removing j^{th} coordinate. The objective is to maximize the payoff of all buyers from the chosen outcome as stated in Eq. (8a). Here z is total number of buyers.

$$\max \textstyle\sum_{j_b=1}^{z} P(v_{j_b}) \tag{8a}$$

$$P(v_{j_b}) = e_s(V^*) - e_s(V^*_{-j_b}) + r_{j_b}(V_{-j_b}) \tag{8b}$$

$$s.t.\ e_s(V^*) = v^{*1} + v^{*2} + v^{*3} \ldots. + v^{*z} \tag{8c}$$

$$e_s(V^*_{-j_b}) = v^{*1}_{-j_b} + v^{*2}_{-j_b} + v^{*3}_{-j_b} \ldots. + v^{*z}_{-j_b} \tag{8d}$$

$$r_{j_b}(V_{-j_b}) = \textstyle\sum_{w=d'+1}^{z-1} (-1)^{w-d'-1} \left[\dfrac{d' \times L(z, d')}{kL(z, d')(v^{*w}_{-j_b})} \right] \tag{8e}$$

$$L(z, d') = \binom{z-1}{d'} / B^{d'}_{z-1} \tag{8f}$$

$$v_{j_b}(q) < c_g(q) \quad \forall i \in S \tag{8g}$$

Payoff $P(v_{j_b})$ of a single buyer j_b is calculated in Eq. (8b). $e_s(V^*)$ is efficient surplus based on permutation of valuation profile v of all the players shown in Eq. (8c). $V^*_{-j_b}$ is obtained by deleting j_b^{th} from permutation of valuation profile shown in Eq.(8d). $r_{j_b}(V_{-j_b})$ is a rebate function indicating a partial refund to a buyer who has overpaid for utilities and to motivate him for participation. Rebates are given to the buyer j_b, which helps to reduce budget imbalance of the mechanism. Rebates for buyer j_b are dependent on profile types of other agents, and not on the valuation of buyer j_b, It is calculated in Eq. (8e). In Eq.(8e), d' is the identical objects means total number of available electricity units at seller site for which buyer j_b submit valuations.

$L(n, d)$ is the calculation of efficiency function of OECS. It depends on binomial distribution of total objects and number of participants is calculated using Eq. (8f). From the above payoff, it is clear that it totally depends on the valuation profile of the buyer and other participants. To win with maximum payoff, SMU have to select minimum valuation value. It would be in favor of buyer to select valuation, which is less than the cost imposed by grid (for demanded quantity of electricity (q)) without playing game. The valuations, $v_{j_b}(q)$ submitted by buyer j_b to get quantity q should be less than the cost, $c_g(q)$ to get that quantity q directly from grid using TOU tariff shown in Eq. (8g).

The cost of player j is reduced after achieving the objective (8b). The payments made by winner buyers are calculated in. Eq. (9).

$$p_g^{j_b} = \sum_{j_b=1}^{z} (v^*_{-i} \times q)_z - \sum_{j_b=1, j_b \neq i}^{z} (v^*_i \times q)_j \tag{9}$$

The payment calculation in (9) is the part of objective function in (4d). The payment of buyer j_b consist of two parts. In first part, sum of valuation of all the buyers multiplied by their quantity q (mentioned in the energy valuation vector of each buyer) till the end of total available quantity d is calculated excluding buyer $j_b's$ valuation. In second component welfare of other players from the chosen outcome of buyer j_b is calculated. In OECS, rebate function play the role of budget balancing. In a mechanism design budget balancing is also very important with all other properties including efficiency allocation, incentive compatibility and individuality rationality.

The novelty features of OECS as compared from previous studies [20], [32], [44], [45] are as follows:

- OECS not totally depends on the user's truthful information about future demand, the system start working based on the predicted load of upcoming hours of each user, which were not considered in the previous works.
- In [20], [44], the model did not consider electricity generation from renewable energy resources at local level. OECS consider the costs of generating electricity from in-house mini micro-grid and from neighboring micro grids.
- OECS also prefer to get electricity from neighboring SHU's to reduce electricity transmission cost, that was not considered in literature.
- The previous work in [20], [32], [44] and [45] also considered the energy consumption scheduling for demand side management, based on VCG mechanism but have not considered the budget imbalance property of VCG mechanism. It inherently, imposes problem of budget imbalance but OECS calculates a rebate function using Moulin mechanism in (8e) to overcome these problems and ensure user participation.
- In this research, OECS calculates the tentative electricity bill for each SHU's one hour prior actual usage time slot. System also shows difference in electricity bills with and without using OECS, which were not considered in any previous works.
- The electricity bill calculated using OECS mechanism is reduced as compared to other systems presented in [20], [32].

IV. PERFORMANCE EVALUATION

Performance of OECS is evaluated from multiple aspects, as described below:

TABLE 1. Comparison of different existing mechanisms.

Social Choice Function	Allocative Efficiency	Budget Balanced	Dominant Strategy Incentive Compatible	Individual Rationality
First Price Auction [46], [47]	Yes	No	No	Yes
Vickrey Auction [46], [48]	Yes	No	Yes	Yes
Vickrey Clarke Groves (VCG) Auction [49], [34]	Yes	No	Yes	Yes
OECS mechanism	Yes	Yes	Yes	Yes

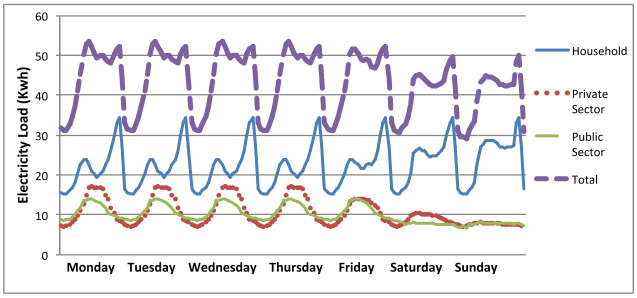

FIGURE 2. Weekly load profile of user according to categories of users, used during simulation [38], [40].

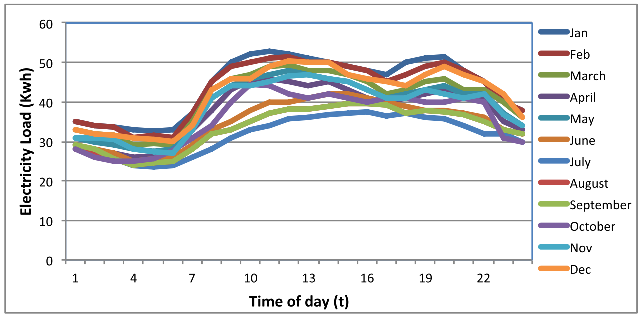

FIGURE 3. Monthly load profile of user according to time of day, used during simulation [38], [39].

1) Comparison of OECS with existing mechanisms using same attributes is performed.
2) Load Prediction Accuracy: Accuracy of the *PL* is calculated by comparing it with the actual load for time interval (t).
3) Electricity Bill: This represents the electricity bill of individual buyer calculated in (4c) compared with other two systems. The tentative bill with and without using the system and their difference with actual electricity bill of each SHU is also evaluated.
4) Efficiency: Efficiency of the OECS mechanism with the increase of consumer's participation is observed; agents behave as consumers in the simulation model.
5) Payoff: Payoff of every SHU is calculated and compared with a threshold.
6) Budget Balanced: This is very important property which considers that none of the participant ends up with problem of budget imbalance. This shows that how the OECS mechanism is better in term of total budget of all the participants as compared to other approaches used in [20], [32], [44].

The comparison of different existing auctioning mechanism with OECS is given in Table 1. Allocative efficiency ensures that production of electricity presents consumers preferences. Moreover, marginal benefit of consumers is equal to the marginal production cost. A budget-balanced property is used to ensure that no participant end up with deficit or negative surplus. Budget balancing of OECS is less than existing mechanisms as rebate is calculated in OECS and given to the electricity consumers in the form of budget surplus to overcome deficit if any. Dominant Strategy Incentive Compatible (DSIC) is also achieved because every user can reduce electricity bill by acting on true valuations only. This is the same property hold by VCG as OECS also preserves the properties of VCG mechanism. Individual rationality imposes that each user can obtain more benefits in term of cost reduction when they individually submit valuations as compared to submit combine valuations of each cluster.

The hourly load profile is an important input for OECS system. To achieve, this goal the performance of load prediction module is tested. Typically, electricity demand varies over days, weeks and months. Moreover, monthly data variation also reflects the changes in weather therefore weather is not considered separately in this validation. With hourly metering of electricity consumption by individual customers, a large amount of data has become available. In this work, accuracy of *PL* is tested by agent based weighted average prediction algorithm [37]. The whole day is divided into 24 hours time slots. Electricity load prediction performs one-hour prior to the actual time interval. To calculate the predicted load for time slot t, forecaster agent calculates PL_t^j; the upcoming predicted electricity load of consumer j for time slot t.

Furthermore, the agent based weighted average prediction algorithm is based on two factors experts agents' advise and associated weights. To calculate experts advise, Anderson model [38], [39] is adopted which uses electricity load aggregation technique based on the categories of electricity consumers. The data varies according to months, weekdays and weekends. Expert agents choose advise with some variation from the aggregated data given in Fig. 2 and Fig. 3.

Data for hourly electricity consumption is available at the **Danish Energy Association**. A description of the benchmark data is found in [38], [40], [50]–[52]. The electricity load profile depends on the categories of users (household, public sector, private sector) as shown in Fig. 2. Monthly load profile is shown in Fig. 3. The data is imported into MATLAB for simulation of load prediction module to train agents for advice. Initially 8 experts are considered, having some weights in a range of (1-5). PL_t^j for a single smart home user is calculated using Eq. (1).

For comparison of actual and predicted load, mean value of both predicted and actual load of all users according to time is given in Fig. 4. Fig. 4 shows that there is a minor difference between actual and predicted load. To re-assign the weights of experts, actual load is compared with the advise of every

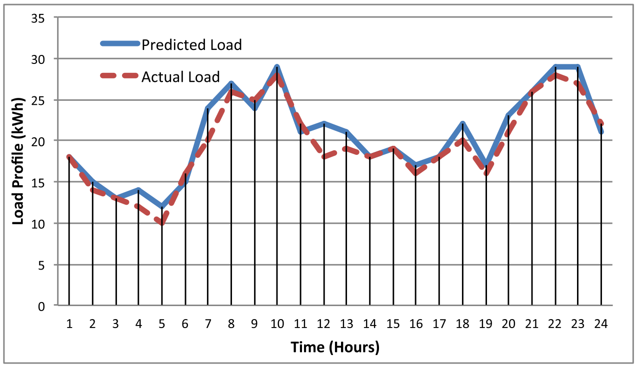

FIGURE 4. The comparison between actual and predicted load of electricity according to time of the day.

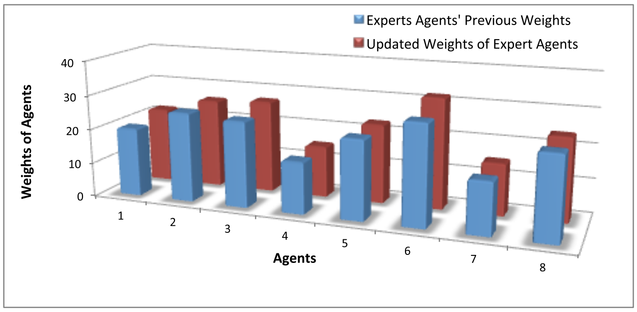

FIGURE 5. Agents' weights re-assignment algorithm' outcome: The difference between expert agents' previous and updated weights.

TABLE 2. Data about agents: valuations given by each agent for their specified amount of electricity units.

Agents	Units Required	Valuation of Agents
1	2	59
2	4	20
3	1	7
4	4	29
5	4	69
6	4	27
7	1	51
8	2	30
9	2	45
10	3	32
11	1	62
12	3	46
13	1	36
14	3	61
15	2	22
16	4	47

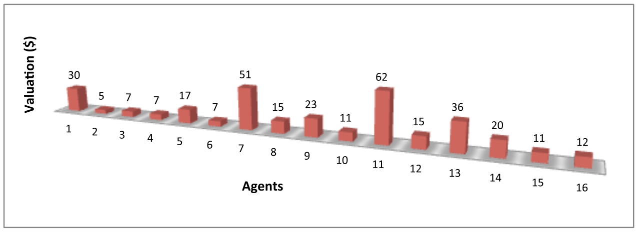

FIGURE 6. Valuations submitted by agents against each unit.

agent and increase the weights of experts according to the accuracy of their prediction using Algorithm 1. Comparison of experts weights before and after the implementation of Algorithm 1 is shown in Fig. 5. It is clear from the Fig. 5 that weights of agents are increased whose prediction was close to the actual load.

This research is conducted to minimize the electricity cost of SHU's. For simplicity, same SHUs are considered whose load is predicted in the previous module. Furthermore, the cost of energy is high at the start of the day and also at evening. Moreover, It is assumed that if electricity is demanded from the electricity supply company directly (grid station) without playing game then the cost function is 0.7 (8 AM-2 PM), 0.4 (2 PM-7 PM), 1 (7 PM-12 AM), 0.3 (12 AM-5 AM), and 0.4 (5 AM-8 AM). This data is taken from Samadi, [19], [20]. First the cost to get *PL* from each smart home mini micro-grid C_h is calculated in [43]. According to OECS, each SHU prefer to buy electricity from their adjacent neighbors within a cluster. Cost to get electricity from adjacent neighbors C_n is calculated in [43]. To fulfill further demand each SHU's agent submits his valuations against remaining quantity of electricity to the sellers and electricity trading will start.

The data used for simulation is shown in Table 2 and Table 3. Table 2 shows agent index (agents are working on behalf of SHU's), required units of electricity and valuations submitted by each agent. The valuation of agents differs based on their needs. The valuation for each agent is plotted in Fig. 6. To define a threshold, two different systems are compared with OECS. First, system without OECS in which demands of each electrical appliance of every SHU are assumed to be fulfilled by electricity supply company only (grid station). Second system is based on VCG mechanism proposed in [20]. The simulation results of electricity cost of each SHU by using OECS, without OECS and VCG based system are depicted in Fig. 7. It is clear from the results that there is a significant difference in electricity bill of same SHU by using three different systems. Electricity bills for SHU's are reduced by using OECS.

The loss in efficiency incurred by using OECS is calculated using (8f) shown in Fig. 8. To calculate efficiency loss, the binomial of the r identical objects based on n agents is calculated, and the formulation of efficiency loss is performed based on OECS mechanism.

Comparison of the OECS with the previous studies is also performed. Table 3 shows the winner agents, based on their valuation. By comparison, it is clear that the payoff of every participant is improved using OECS, as can be inferred from Fig. 9.

To test the budget imbalance property of OECS mechanism, data is considered from same simulation values given in Table 3. Same parameters are used to compare budget imbalance of OECS with other published mechanism like groves mechanism [20]. The difference is shown in Fig. 10. It is clear that budget imbalanced of OECS is reduced as compare to other work done in this domain. It is also clear from Table 3 that the payoff of OECS is high when compared to

TABLE 3. Information about winners; Their valuations, payments, payoff and comparison of budget imbalance using different mechanisms; VCG and OECS.

Winners Agent's Data								
Units Required (KW/hr)	Valuation of agents ($)	Per Unit Vauation ($)	Units Provided (KW/hr)	Values of agents	Payments of Winners	Payoff using VCG	Payoff using OECS	Budget Imbalance of Mechanism($)
2	59	29.5	2	59	34.5	24.5	32.8333	OECS ; 43
4	69	17.25	2	34.5	30.6667	3.8333	12.1667	
1	51	51	1	51	17.25	33.75	37.9167	
2	45	22.5	2	45	34.5	10.5	18.8333	VCG ; 90
1	62	62	1	62	17.25	44.75	48.9167	
1	36	36	1	36	17.25	18.75	22.9167	
3	61	20.3333	3	61	49.8333	11.1667	23.6667	

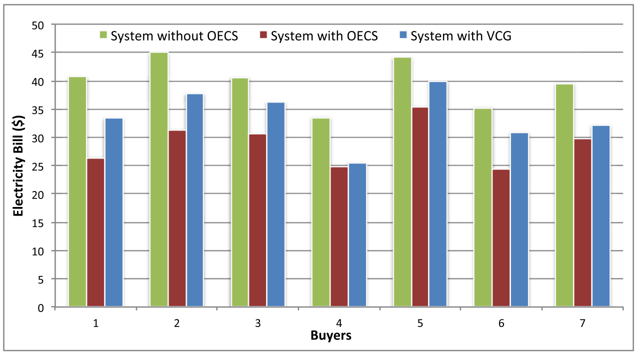

FIGURE 7. Comparison of electricity bills of buyers using different systems.

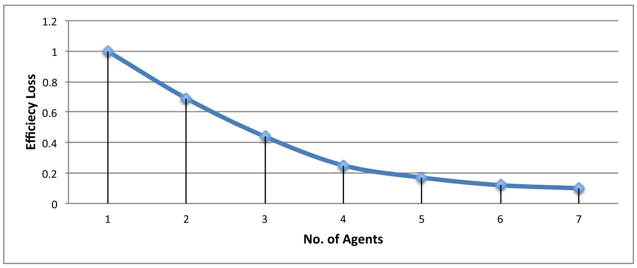

FIGURE 8. Efficiency loss of the proposed system.

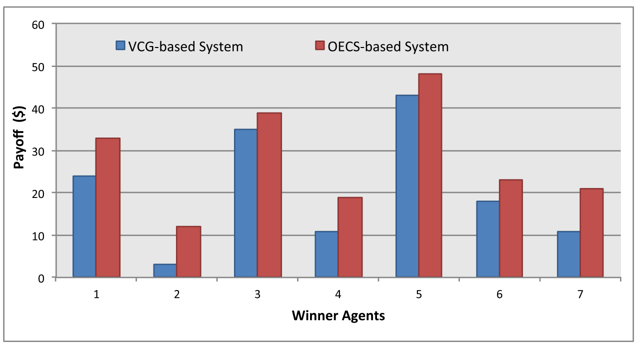

FIGURE 9. Comparison of agent's payoff with Vickrey Clarke Groves (VCG) approach and budget balanced optimal energy consumption scheduling mechanism (OECS).

other mechanisms. Similarly, Table 3 also shows that budget imbalance using OECS is less than previous research.

The tentative electricity bill of all SHU's is also calculated based on their predicted load. To motivate the electricity

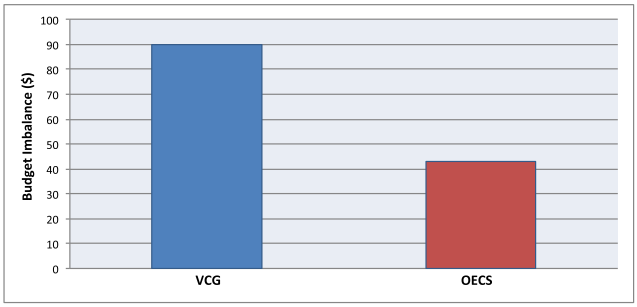

FIGURE 10. Comparison of budget imbalance of both mechanisms: VCG and OECS.

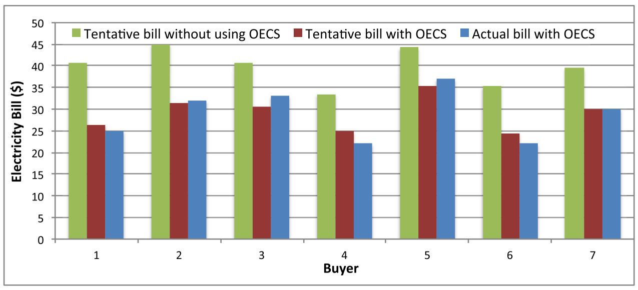

FIGURE 11. Comparison of tentative electricity bill with and without using the OECS.

consumers for participation the difference between their tentative electricity bill with and without using the system is also provided to users using AMI. The difference between tentative and actual bill is also shown in Fig. 11.

V. CONCLUSION AND FUTURE WORK

In this research, an auctioning scheme is modeled to consider both SHU's and suppliers. A weighted average prediction algorithm was designed to forecast loads and share that information among multiple electricity suppliers. In response to the submission, energy trading is performed based on OECS. The properties of the auctioning mechanism were analyzed, and the results show that OECS possesses the properties of allocation efficiency, dominant strategy and incentive compatibility, as well as being budget balanced. From extensive simulation results, it is concluded that by implementing OECS, SHU's will benefit from a reduction in electricity bills and an increase in payoff. The auctioning scheme also proved beneficial for energy suppliers by reducing their PAR. System stability is achieved by reducing efficiency loss with increase in participation from the consumers.

In future, OECS can enhance performance by using benefits of recent research done in sensor-based system in smart grid as proposed in [53], [54]. OECS could be implemented by sensor based IoT enabled system, which can transfer optimized electricity cost information of each consumers using cloud data storage. Moreover, the effect of smart sensing mechanism in electricity consumption scheduling could also be considered. Multiple other risk factors including system failure and recovery from failure could also be considered to make the OECS more energy efficient and stable in all possible circumstances.

COMPETING INTERESTS

The authors declare that there is no conflict of interest regarding the publication of this research work.

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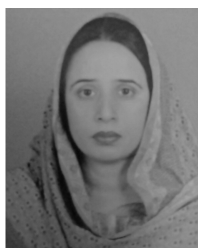

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