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RESEARCH ARTICLE

A Computationally Efficient Method for Energy Allocation in Spot Markets With Application to Transactive Energy Systems

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ABSTRACT Spot markets provide an interesting opportunity for profit maximization by energy trading based on immediate decisions on participant bids. However, their short market-clearing time can affect computational efficiency, search space, and reliability of price-energy allocation to bidding participants. Accordingly, developing a prompt and effective decision-making process plays a vital role in smooth energy delivery in these markets. This paper proposes an approach to alleviate the computational cost of the spot market aggregator in order to decide price-energy bids. The proposed bidding model is developed for the transactive energy systems, where the spot market aggregator utilizes the proposed method to maximize profit by choosing participants' demand-side bids. The proposed method can efficiently manage participants' combined energy and price information and avoid a highly complicated search space. It takes advantage of the multi-variable Taylor series approximation to create users' individual cost functions. The approximated cost functions lead to user-specific bids that expedite the spot market transaction while maintaining aggregator profit. The resultant system is able to exercise profit maximization with high performance within milliseconds. The efficiency of this scheme is also demonstrated through a comparative study by using the particle swarm optimization method.

INDEX TERMS Transactive energy, spot markets, combinatorial auction, smart grids, computational efficiency, demand response.

NOMENCLATURE

INDICES

i	House index.
j	Price point index.
k	Time-step index.

PARAMETERS

q^i_{max}	Maximum heating capacity.
x^i_{min}	Minimum indoor temperature.
x^i_{max}	Maximum indoor temperature.

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VARIABLES

δ^i_{k+1}	Preference of residential house.
π_j	Set of price points.
M	Number of price points.
N	Number of RAs.
q^i_j	Energy demand set.
q^i_{k+1}	Energy demand.
u^i_j	Binary decision variable.
$x^{ext,i}_{k+1}$	External temperature.
x^i_k	Internal temperature.
x^i_{ref}	Reference temperature profile.

FUNCTIONS

$\bar{x}_i$	Average energy demand.
$C(y)$	Original cost function.
C_{aprx}	Approximation of cost function.
U^i_{k+1}	Utility function.

ABBREVIATIONS

ACO	Ant Colony Optimization.
BESS	Battery Energy Storage System.
CCA	Conventional Combinatorial Auction.
CVaR	Conditional Value at Risk.
DSO	Distribution System Operator.
GA	Genetic Algorithm.
HEMS	House Energy Management System.
PHEVs	Plug-in Hybrid Electric Vehicles.
PSO	Particle Swarm Optimization.
QUBO	Quadratic Unconstrained Binary Optimization.
RA	Residential Agent.
TCL	Thermostatically Controlled Loads.
UPA	Uniform Price Auction.
WDP	Winner Determination Process.

I. INTRODUCTION

A. BACKGROUND AND MOTIVATION

The emergence of transactive energy systems is a key enabler for substantial end-users' participation in future local electricity markets. Under the smart grid paradigm, such frameworks facilitate participants' access to a variety of transactive market mechanisms. These procedures are mainly established by forward and spot electricity markets, popular for electricity trading [1]. In the former, the energy is procured for future delivery to customers while in the latter, it is provided for immediate usage [2]. Instant trades of a spot market are made within a short duration from five to fifteen minutes and normally take place before real-time energy exchange. Accordingly, they can bring about opportunities for energy providers, specifically aggregators, and consumers. In the context of spot markets, aggregators can interact with customers more frequently, thus boosting trading profits [1]. Besides, they can help users play a dynamic role by bidding and taking advantage of the variation of real-time wholesale energy price, which is not the case in schemes with typical billing contracts. Consequently, customers can reduce their costs in this type of energy market [3].

In the electricity market, most of the energy trading is carried out through an auction-based approach [4], [5], where the aggregator can trade by exploiting different strategies with consumers in spot markets, including combinatorial double auction [6] and single-sided auction [7]. In a combinatorial double auction-based market, the aggregator determines a winner based on the bids placed for desired items by multiple buyers and the offers placed by the sellers to sell the items [8]. This determination of the winner is popularly known as the winner determination process (WDP). The combinatorial single-sided auction is a double auction variant, consisting of multiple buyers and only one seller or vice versa [8].

In the combinatorial single-sided auction, the aggregator evaluates all possible bidding combinations placed by buyers. As the number of buyers increases with the number of bids, the possible combination increases significantly. Consequently, the WDP becomes computationally costly because the aggregator is unaware of the best possible bid to accept from each consumer before evaluating all possible combinations. Owing to the vast search space, the combinatorial auction suffers from high computational complexity [8]. The WDP of a combinatorial single-sided auction can be represented by quadratic unconstrained binary optimization (QUBO) [9] and 0-1 knapsack problem [10]. This problem is difficult to solve due to the computational complexity [11]. The WDP of combinatorial auction is a well-known NP-hard problem [8], [12], which is a arduous problem to solve in the short time duration of five to fifteen minutes because the aggregator needs to look in all search space before choosing the possible combination of the bid. The spot market has a short duration, between five to fifteen minutes, and takes place before real-time energy exchange [13], [14]. Due to such an operational limitation, the decision-making time is vital to the aggregator of this electricity market [15], [16].

B. LITERATURE REVIEW

In recent years, different research works have been carried out to improve the operation of spot markets by maximizing the profit of their participants [20]. In [21], the authors studied the energy allocation problem in spot market to maximize the profit of different electric utilities considering participants' bidding strategy. The authors in [22], proposed optimal portfolio selection theory based approach for managing electricity suppliers' risks in spot market. However, their method faced difficulties in accurately estimating probabilistic distributions of electricity market prices. A short-term decision-making model based on the conditional value at risk (CVaR) measure was proposed in [23] to deal with real-time electricity retailers' hourly bidding risk. They used Battery Energy Storage System (BESS) to provide flexibility; however, the suggested method did not address the associated bidding risk.

In [24], the bidding and offering framework was presented for a hybrid power plant comprised of photovoltaic, wind, battery energy storage and compressed air energy storage in intraday and day-ahead markets. They developed a stochastic-interval framework based on a mathematical formulation that considered uncertainties related to stochastic and interval parameters. Besides, the intraday and day-ahead dispatch model for profit maximization of an integrated biomass-concentrated solar system was developed [25]They used CVaR to control risk over profit distribution, and Information Gap Decision Theory (IGDT) was used to consider solar-related uncertainty. The authors in [26] used a CVaR-based trading strategy to maximize intraday and day-ahead market profit. In [27], the strategy for energy arbitrage of BESS in day-ahead and intraday markets is presented. They controlled the risk of uncertainty in market

TABLE 1. Similar elements of combinatorial auction process according to relevant literature.

Reference	Application	Market Structure	Combinatorial Auction Type	Bidding Language	Methods
[6]	Multiple micro grid trading	Day-ahead markets	Double auction	XOR	Genetic algorithm and Particle swarm optimization
[7]	Energy storage sharing	Intra-day markets	Single-sided auction	XOR	Hybrid evolutionary algorithm
[17]	Load shedding management	Day-ahead markets	Distributed auction	XOR	Particle swarm optimization and Hybrid genetic algorithm
[18]	Shared energy storage	Day-ahead markets	Distributed auction	XOR	Fully polynomial time approximation scheme
[19]	PV systems	Spot markets	Double auction	-	Bids Matching
This work	Thermostat control load	Spot markets	Single-sided auction	XOR	Multi-variable taylor series approximation

prices by the proposed second-order stochastic dominance constraint based on a fuzzy decision-making manner.

A stochastic resource planning scheme for Plug-in Hybrid Electric Vehicles (PHEVs) charging was studied in [28], which aimed at handling price uncertainties in a spot market. Unfortunately, this strategy did not consider the impact of PHEVs demand on the power system operation. The authors in [29] utilized the Cournot game model to describe the bidding of different generation companies. Although their method optimized generation assets, it mainly focused on market procedures on the generation side rather than the end-user side. In addition, the study [30] was carried out in the context of a distribution company for the optimal solution for energy purchase in the Philippines wholesale electricity spot market (WESM). Their procedure did not consider how participants' demand uncertainty affected the distribution company. Likewise, the authors in [31] analyzed the Italian spot market for resource allocation problems that maximized the participated players' profit; however, they did not consider residential consumers. The comparative study in [32] and [14] was carried out for the energy market participation problem in the spot market context. The economic models based on bidding and allocation problems were vastly studied in the literature for computing and resource management [33]. The multi-objective genetic algorithm was proposed in [34] for combinatorial reverse auction of renewable energy. Here, the computation time and accuracy results were compared with the branch-and-bound heuristic method. Moreover, in [35], the WDP was solved for the players with energy demand in the combinatorial auction. The multistage stochastic optimization model was proposed in [36] for the combinatorial bid problem of different generation companies in electricity spot markets.

Several attempts have been made to cope with the challenges of optimal resource allocation with minimal computation time [37]. In this context, a heuristic algorithm based on the Lagrangian decomposition [37] was implemented on the flexibility market for demand response action. Also, a combinatorial auction approach was developed in [18] for the community that participated with the energy storage operator. The energy storage operator in [18] solved the NP-hard WDP by exploiting a fully polynomial-time approximation scheme that maximized social welfare. The energy shared among households through the XOR bid was solved by the hybrid Particle Swarm Optimization-Genetic Algorithm (PSO-GA) approach in [7] with a computational time of more than 2 minutes for 30 houses. Unfortunately, the PSO-GA approach becomes unsuitable for a significant number of houses in the time slot of five to fifteen minutes [7].

In [6], the WDP for XOR bid in multiple microgrid trade was solved by the meta-heuristic method for up to 30 bidders. The double auction problem [6] can be reduced to a combinatorial single-sided auction [7] by considering only one seller with energy storage and multiple household buyers participating with the auctioneer for trade. The authors [38] proposed a method to find the Nash equilibrium via decomposition of combinatorial optimization process using Walsh-Fourier transform in electricity and natural gas markets. However, with the increased number of participants, it becomes computationally intensive. The hybrid genetic algorithm was proposed in [17] for the demand management in a microgrid, where the participants used XOR bids. However, the solution got saturated for a large number of users [17]. The winner determination problem for the combinatorial auction was solved by a meta-heuristic approach like the hybrid ant colony algorithm [39]. The authors in [40] proposed a hybrid Ant

Colony Optimization (ACO) algorithm to solve the NP-hard nature combinatorial auction problem at the expense of more execution time. In [41], a heavy-head sampling strategy was proposed with Imitation Learning (IL) to solve the WDP of combinatorial auction. They proposed IL used with Reinforcement Learning (RL) to improve the evaluation process of CA; however, it is prone to extended training time.

Likewise, the Improved Partheno-Genetic Algorithm (IPGA) was proposed for the combinatorial auction. However, when the number of users increased by 50, the execution time increased substantially, which is not feasible in very short-time spot markets [42]. The most exploited meta-heuristic algorithm, the Particle Swarm Optimization (PSO), with its many modifications was also reported to suffer from the drawback of early convergence [43]. Despite its popularity, PSO's major shortcoming reported [44] is the need for more computational time with no guarantee of a global maximum point.

The above literature survey suggests that heuristic methods are exploited to solve the WDP of the combinatorial auction for short and days ahead market. The limitations identified from the previous work are:

- Dependency on meta-heuristic methods for solving combinatorial auction has no control over the number of iterations to achieve the best solution.
- Increase in computational time with increasing participants exceeds the limitation of the time slot of the spot market.
- The profit yield for the aggregator varies when solving via meta-heuristic methods for the same time slot of the spot market.

C. CONTRIBUTIONS AND ORGANIZATION

For the aforementioned reasons, this paper presents an appealing approach to minimizing the computational time and achieving optimal profit earnings in the spot market context. Note that, the residential houses in the proposed work fall into the combinatorial single-sided auction category owing to the fact that many buyers need energy from one seller. For the brevity of presentations, Table 1 compares the proposed work with relevant literature on the elements of the combinatorial auction. The main contributions are summarized below:

- Computational time: A multi-variable Taylor series approximation-based solution to the NP-hard problem of WDP for combinatorial single-sided auction in the spot market. That results in shorter computational time even in the presence of an increased number of users.
- Near to global profit: Efficient energy allocation for different residential houses based on their bidding profiles in the spot market. That enables the aggregator to earn an optimal profit near the global profit point.
- Deterministic solution: The proposed methodology helps the aggregator to achieve deterministic solution for the profit in each time slot of the spot market.

The rest of the paper is organized as follows. Section II discusses the model of the system. Section III formulates and discusses the aggregator allocation process. Section IV presents the simulation results. Finally, the paper is concluded in Section V.

II. MODEL OF THE SYSTEM

We consider a community consisting of multiple residential consumers and a spot market aggregator. The spot market process consists of five to fifteen minutes slot and takes place before the real-time energy consumption [19]. The spot market aggregator's objective is to maximize profits. Each residential consumer is equipped with an intelligent home energy management system capable of controlling their flexible loads. Also, these residential consumers are assumed to have a reliable communication system, which allows for sending and receiving information. Note that each residential consumer has a different building model, and the preference for comfort versus energy saving is different for each user in each time slot.The Fig. 1 illustrates the interaction mechanism between the transactive energy distribution grid's demand-side management agent and residential consumers in the spot market context. Here, the residential consumer receives first a set of price point information from the spot market aggregator. Based on price points from spot market aggregator, exogenous data, building model and their preference, each residential consumer solves the convex optimization problem against each price point to generate corresponding energy demand. After solving against each price point, the residential agent organizes and transfers their price-energy bids to the spot market aggregator using bidding structure. There are mainly two bidding structures commonly known as single-bid and combinatorial bid structures. The bidding language used in this work is exclusive OR (XOR), which falls into the combinatorial-bid structure. The combinatorial-bid structure differs from the single-bid structure since atomic bid is the most common language to express in a single-bid structure [45]. In a single-bid structure, the bidder can submit only one pair of a bid using atomic bid language represented by (π_1, q_1), where q_1 is the energy demand for the next time spot, and π_1 corresponds the price the bidder wants to pay. On the other hand, in a combinatorial-bid structure, there is no restriction on the bidder to submit only one pair of the bid (known as an atomic bid). Consequently, the bidder can submit multiple atomic bids using OR or XOR language [46]. In OR bid language, participants can bid to receive more than one item in an auction. If the participants submit the bid using OR bid language, the spot market aggregator, after solving WDP, can select more than one bid pair from the bidders' transmitted set. However, in XOR bid language, the bidder can win at most one bid in an auction. In this work, the residential consumer transmits the bid using XOR bid language. That is because the market slot is of concise time duration, and for the next time slot, the residential consumer can consume only one of the transmitted energy demand bidding pairs.

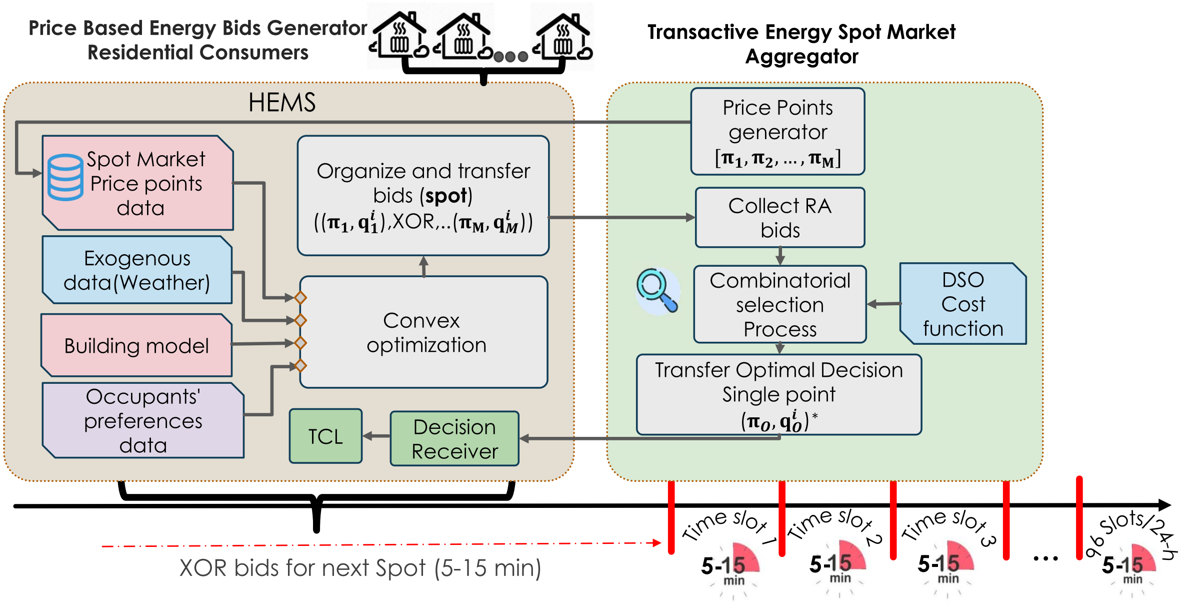

FIGURE 1. Spot market aggregator decision process based on residential agents bids.

The spot market aggregator collects all residential agents' bids before starting the combinatorial selection process. Based on the collection of bids and the Distribution System Operator (DSO) cost function parameter received at each time slot, the spot market aggregator generates all unique possible combinations. Each possible combination is evaluated for the corresponding profit that the aggregator can earn. Consequently, the aggregator selects a unique price-energy bid for each residential consumers from their transmitted price-energy bidding vector, maximizing the aggregator profit.

A. ASSUMPTIONS

The work of this paper is based on the following assumptions:

- The distribution grid infrastructure is constraint-free and capable of providing energy to all connected residential consumers as per the contracted maximum energy capacity [47]. Also, a reliable communication link across the system exists for transferring and receiving the information.
- For each time slot, the spot market aggregator receives the cost function parameters from DSO and demand bids from RAs only once before each time slot. The parameters and bids remain the same for a particular time slot of the spot market.
- The RAs transmit their energy demand against the price points that are provided by the spot market aggregator. The spot market aggregator will consider only those RAs energy demand bids that are against its transmitted price points.

B. AGGREGATOR AGENT

The aggregator agent transmits set of price points $\mathbf{P} := \{\pi_j, j = 1, \ldots, M\}$ to a neighborhood composed of N residential agents for each fifteen minutes time slot before the real-time energy exchange starts. The price vector $\mathbf{P}$ is same for all residential agents. Let $\mathbf{Q}_i := \{q_j^i, j = 1, \ldots, M\}$ represents the set of energy bids transmit by the i^{th} house from a residential group of N buildings. Each element q_j^i denotes the energy consumption demand by each residential agent against each price point in set $\mathbf{P}$ respectively. In general, there are two types of bids: atomic bids and XOR combinatorial bids [48]. The atomic bid format uses a single pair of bid, where each i^{th} residential agent (RA) can transmit only a single pair (π_1,q_1^i). On the contrary, in the combinatorial bid format the RA can submit multiple pairs of (π_j,q_j^i), where π_1 is the price, and q_1^i is the corresponding energy demand for the next time slot. Interestingly, these multiple pairs in the combinatorial bid format are combined by XOR-type logical bidding, which is expressed as $(\pi_1, q_1^i)\, XOR \ldots XOR\, (\pi_M, q_M^i)$ [46]. This means that the spot market aggregator can only select one pair from all the submitted XOR bids by the RAs, which can significantly maximize the spot market aggregator's profit. Accordingly, the aggregation of energy y becomes the sum of allocations for N participants in the spot market

$$y = \sum_{i=1}^{N} \sum_{j=1}^{M} u_j^i q_j^i, \tag{1}$$

where for i^{th} RA the u_j^i is a decision variable taking binary values. In each bid evaluation, u_j^i takes the value 1 for a specific j^{th} bid in $\mathbf{Q}_i$ and 0 is assigned for rest of energy bids. The WDP of XOR bids that can maximize the aggregator profit is expressed by the following integer programming problem [49]

$$\underset{u_j^i, \forall i \in I, \forall j \in J}{\text{Maximize}} \sum_{i=1}^{N} \sum_{j=1}^{M} u_j^i q_j^i \pi_j - C\,(y)$$

$$\text{s.t.} \sum_{j=1}^{M} u_j^i = 1,$$
$$u_j^i \in \{0, 1\}, \tag{2}$$

where $C(y)$ represents a non-linear cost function providing the selected aggregated energy. Profit-maximizing optimization problem is formulated as an index search problem that looks between 0 and 1, trying to select the best binary decision which corresponds to the index of XOR-type bids [50]. The optimal allocation determination in (2) having quadratic cost function is also known as quadratic unconstrained binary optimization (QUBO) [51]. The aggregation of energy y is the element wise function of the vector Q_i, which makes the terms q_j^i non-separable in (1). As a consequence, the aggregator needs to select only one bid from the XOR-type bid set for each residential consumer. Thus, this non-separable behavior of terms q_j^i contributes to the complexity in the spot market aggregator optimization problem (2). Section III of this paper contains the proposed approach to ameliorate the complexity associated with the optimization problem containing non-separable terms.

C. RESIDENTIAL AGENTS

The spot markets are the transactive energy markets in which residential agents participate just before the real-time energy exchange. Since this process takes place in concise time duration, the transfer of demand bids and the allocated price-energy pair just before every time slot is of prime importance. As shown in Fig. 1, each RA is equipped with an intelligent system HEMS, to facilitate its participation in the transactive energy spot market. Besides, each RA also consists of an electric heater controlled by a thermostat, which helps them with the flexibility (cost vs comfort) in the spot market. Demand-side bidding is widely used [52], where each residential consumer sends price-energy demand bidding points every fifteen minutes. These bidding points are organized and transmitted in a non-increasing price point manner. The HEMS uses thermostatically controlled loads (TCL) to generate different energy demands against price points; the detailed procedure of demand bids with TCL is presented in [53].

The indoor temperature at the next time spot x_{k+1}^i, in a residential house is given by [54]

$$x_{k+1}^i = \alpha x_{k+1}^{ext,i} + \gamma x_k^i + \beta q_{k+1}^i, \tag{3}$$

where the parameters α,β, and γ obtained through the ordinary least square (OLS) represent the thermal characteristics of a residential house. Outdoor temperature prediction for next time spot is represented by $x_{k+1}^{ext,i}$ and the current indoor temperature is represented by x_k^i. The term q_{k+1}^i represents the energy required for predicting x_{k+1}^i. Each RA has a different preference for comfort and saving [53], [54]. This difference in preference helps them to get flexibility in energy consumption, which is given by

$$U_{k+1}^i = \delta_{k+1}^i (x_{k+1}^i - x_{ref}^i)^2, \tag{4}$$

where x_{ref}^i is the indoor temperature set point for the next time spot. The U_{k+1}^i represents the utility of each residential house achieved by consuming energy q_{k+1}^i depending on its preference δ_{k+1}^i that is comfort versus saving. The generated energy demand encompassing the thermal model of a house is given by [55]

$$\underset{q_{k+1}^i, \forall i \in I, \forall j \in J}{\text{Maximize}} \sum_{i=1}^{N} \sum_{j=1}^{M} (U_{k+1}^i - \pi_j q_{k+1}^i)$$
$$\text{s.t. } q_{k+1}^i \in [0, q_{max}^i],$$
$$x_{k+1}^i \in [x_{min}^i, x_{max}^i]. \tag{5}$$

Each RA participating in the spot market will receive up to ten non-increasing different price points π_j [18], [56], [57]. Based on the user preference, outdoor temperature, indoor temperature and price points, the RA generates corresponding energy demand q_{k+1}^i. Then the RA transmits this price-energy demand profile to the aggregator to maximize his utility function mentioned in (5).

III. AGGREGATOR ALLOCATION PROCESS

In this section, first the problem related to the solving the WDP in a combinatorial single-sided auction process is formalized. Then, the proposed approach to tackle the issue is presented.

A. PROBLEM FORMULATION

The coupling effect in the non-linear cost function (2) poses a limitation contributing to an increase in computational complexity of the combinatorial single-sided auction WDP. The first part $\sum_{i=1}^{N} \sum_{j=1}^{M} u_j^i q_j^i \pi_j$ is the revenue term that the aggregator will earn after selecting specific bid for each house; this term is the linear sum after selecting unique pair from each RA. The second term is the cost for allocating the aggregate of selected energy demand. Here, there arises two possibilities: (i) a linear case $\sum_{i=1}^{N} \sum_{j=1}^{M} u_j^i q_j^i \leq Q_{max}$, where any given combination of aggregated energy is bounded below the maximum energy Q_{max} of the power system and (ii) a non-linear case $C(\sum_{i=1}^{N} \sum_{j=1}^{M} u_j^i q_j^i)$. Particularly, the non-linear cost function is quadratic in nature for the Conventional Combinatorial Auction (CCA) [55], [58], which is formulated as

$$C(y) = ay^2 + by + c, \tag{6}$$

where $C(y)$ is the aggregator original quadratic cost function for supplying the aggregated energy demand with the coefficients $a > 0$ and $b, c \geq 0$. This quadratic cost function is popular because of its tractability in optimization process [58]. The coupling effect of the houses is due to different price-based energy demands in the original quadratic cost function (6) that can be analyzed by expanding it. Alternatively, (6) is recast as

$$C(y) = a \sum_{i=1}^{N} \sum_{j=1}^{N} x_i x_j + b \sum_{i=1}^{N} x_i + c. \tag{7}$$

The terms x_ix_j for $i \neq j$ are non separable or coupling terms, which represent the energy demand against different prices. When N number of houses participates in the spot market, there will be N coupling terms. The profit for the aggregator is the difference between the revenue and cost. The maximum profit in (2) can be achieved by searching relevant combination of the term $\sum_{i=1}^{N}\sum_{j=1}^{M} u_j^i q_j^i \pi_j$ that yields maximum revenue and at the same time a combination of the term $C(\sum_{i=1}^{N}\sum_{j=1}^{M} u_j^i q_j^i)$ that contributes to minimum cost. Subsequently, the aggregator needs to evaluate the non-linear quadratic cost function (6) in the second term of (2) for the same energy terms as appearing in the first term. However, the cost function is non-separable; as a result, the directional optimization cannot be carried out. This makes the optimization problem a NP-hard problem.

B. PROPOSED METHODOLOGY

In order to mitigate this issue, we propose an approximation of the non-linear quadratic cost function via exploiting second-order multi-variable Taylor series approach. The general form for the cost function (6) in multi-variable Taylor series context is given by

$$\begin{aligned} C_t(y) \cong\ & C(\bar{y}) + \frac{\partial C(\bar{y})}{\partial x_i}(x_i - \bar{x}_i) \\ & + \frac{\partial C(\bar{y})}{\partial y_{-i}}(y_{-i} - \bar{y}_{-i}) \\ & + \frac{\partial^2 C(\bar{y})}{\partial x_i^2}(x_i - \bar{x}_i)^2 \\ & + \frac{\partial^2 C(\bar{y})}{\partial y_{-i}^2}(y_{-i} - \bar{y}_{-i})^2 \\ & + \frac{\partial^2 C(\bar{y})}{\partial x_j \partial y_{-i}}(x_i - \bar{x}_i)(y_{-i} - \bar{y}_{-i}) \\ & + \text{Higher Order Terms}, \end{aligned} \tag{8}$$

where $\bar{y}$ represents the aggregated average of each RA transmitted set $\mathbf{Q}_i$ and $C(\bar{y})$ is the evaluation of $\bar{y}$ along (6). The x_i depicts the particular house energy demand set and $\bar{x}_i$ represents the corresponding average energy demand given by,

$$\bar{x}_i = \frac{\sum_{j=1}^{M} q_j^i}{M}. \tag{9}$$

Depending on the $\bar{x}_i$ for each house, the individual cost function will approximate the original cost function by the evaluation point calculated by (9). The $y_{-i} = y - x_i$ indicates all remaining RAs energy demand and $\bar{y}_{-i} = \bar{y} - \bar{x}_i$ corresponds to their average energy demand. Now, to overcome the pernicious effect of the coupling term in (8), we omit the second-order coupling term. As a result, (8) boils down to

$$\begin{aligned} C_{aprx.}(y) \cong\ & C(\bar{y}) + \frac{\partial C(\bar{y})}{\partial x_i}(x_i - \bar{x}_i) \\ & + \frac{\partial C(\bar{y})}{\partial y_{-i}}(y_{-i} - \bar{y}_{-i}) \\ & + \frac{\partial^2 C(\bar{y})}{\partial x_i^2}(x_i - \bar{x}_i)^2 \\ & + \frac{\partial^2 C(\bar{y})}{\partial y_{-i}^2}(y_{-i} - \bar{y}_{-i})^2. \end{aligned} \tag{10}$$

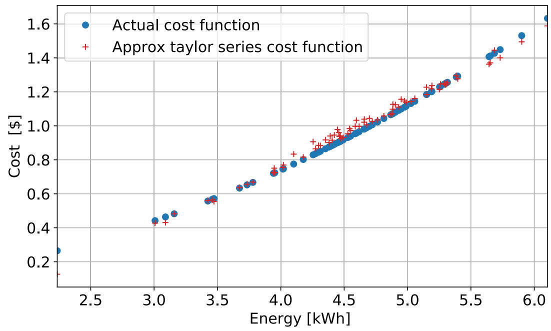

FIGURE 2. Comparison of original cost function with approximate Taylor series function.

Since the cost function (6) is quadratic in nature, the truncated Taylor series approximation (10) of the cost function is limited to second-order. The approach in (10) substantially helps to achieve the separated terms in an additive manner. Precisely, it allows the aggregator to solve the directional optimization (2) and obtain a definite solution as opposed to the heuristic optimization approaches in previous literature.

Utilizing (10), the aggregator calculates the optimal price points allocation individually for each RA without the effect of demand bidding points contributed by other RAs. The proposed individual cost function (10) is independent of the flexible loads that RAs utilize to generate the demand bids, including thermal storage, thermostat control loads, and electrical storage, along with others. Fig. 2 demonstrates the comparison of the original cost function (blue-colored) and the approximate cost function (red-colored) achieved via the proposed approach. In addition, the difference between the approximate and original cost function is shown in Fig. 3. The positive errors in Fig. 3 are beneficial from the aggregator viewpoint. That is due to the fact that the approximate cost function in these cases always creates higher cost then actual cost. On the other hand, the cases with negative errors prove to be beneficial from the consumer view point since such margins lead to bonuses for consumers.

1) COMBINATORIAL SINGLE-SIDED AUCTION

This paper adopts a combinatorial single-sided auction-based market that hierarchically determines the optimal energy. Notably, no negotiation takes place because it is a non-iterative approach. The aggregator utilizes Algorithm 1 to find the best price-energy combination for each RA to maximize the profit. In the combinatorial allocation process, the aggregator will transmit price points to each residential consumer before the next time slot.

Subsequently, each user will generate ten different price-energy demand points based on each user's objective function. Then the users will transmit these demand bidding points to the aggregator. On the aggregator side, after the

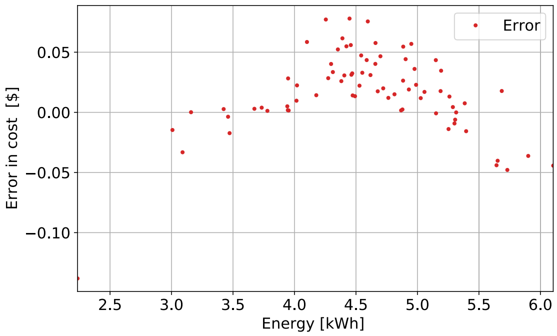

FIGURE 3. Difference of approximate cost function from original cost function.

Algorithm 1 Aggregator Bid Selection Based Energy Allocation

Require: All RAs price-energy demand bidding points.
Step 1: Calculate the evaluation point ($\bar{x}_i$) for all participating RA using (9);
for $i = 1, 2, \ldots, N$ **do**
  for $j = 1, 2, \ldots, M$ **do**
    Step 2: Obtain the individual cost for i^{th} RA using (10);
    Step 3: Get the utility for the i^{th} RA using ($u_j^i q_j^i \pi_j$);
    Step 4: Calculate the profit against each j^{th} price point;
  end
  Step 5: Determine the winning bid for i^{th} RA that yields maximum profit;
end
Step 6: Select specific (π_j, q_j^i) price-energy bid for each house;
Step 7: Allocate the energy to each RA based on step 6.

---

transmission of price points aggregator waits for each RA to send their specific demand bidding points. The aggregator collects all the RA bidding points and then aggregates the demand against each price point. Finally, the aggregator checks all possible unique aggregated energy combinations and chooses the best combination to maximize the profit.

The Step 5 in Algorithm 1 ensures that the spot market aggregator only chooses the bid that gives maximum profit. This is due to the fact that the aggregator wants to maximize its profit. Depending upon the number of price points (denoted by M) transmitted by the spot market aggregator, the aggregator calculates the cost against each transmitted energy demand bid point, with the help of cost function approximation via the Taylor series approach. The aggregator checks profit against each bid combination in Step 4. Based on the profit against each energy bid combination, Step 5 guarantees to choose the bid that yields maximum profit, which is the optimal solution for our work. The proposed Algorithm 1 yields optimal solution by evaluating only $M \times N$ combinations and earning profit closer to the CCA. On the other hand, CCA considered to be a benchmark method for providing an ideal solution for WDP [59] requires evaluating M^N combinations to achieve the maximum aggregator's profit.

Remark: The combinatorial appraoch is capable of delivering unique price-energy point decision for each RA; whereas, the Uniform Price Auction (UPA) [60] decides same price based decision and populates to all the RAs. Interestingly, in UPA, while solving (2) the binary decision variable u_j^i takes the same value ($u_j^1 = u_j^2 = \ldots = u_j^N = 1$) for the j^{th} price point of all the RAs. The aggregator sums up the demand received from each RA with specific discrete price point π_j to calculate the utility $\pi_j q_i$. Subsequently, the cost for energy allocation is calculated using (6). The energy demand q_j^i corresponding to price point π_j, which yields maximum profit is chosen as the decision point. Thus, this makes UPA a special case of the combinatorial approach.

TABLE 2. Aggregator cost function coefficients.

Min(kWh)	Max(kWh)	a	b	c
0	10	0.0137	0.001	0.01
10	20	0.0069	0.001	0.01
20	30	0.0046	0.001	0.01
30	40	0.0034	0.001	0.01
40	50	0.0027	0.001	0.01
50	60	0.0023	0.001	0.01
60	70	0.00195	0.001	0.01
70	80	0.0017	0.001	0.01
80	90	0.00153	0.001	0.01

IV. SIMULATION RESULTS

In this section, the performance of the proposed approach to solve the NP-Hard problem of the WDP is discussed in detail. The time slot of fifteen minutes is considered for the spot market simulations; the fifteen minutes of energy demand data is acquired from the residential houses in a city in Québec province of Canada. The parameters α,β, and γ for the thermal model of the residential houses are obtained from the experimental data recorded by Hydro-Québec. The proposed approach is compared with CCA, UPA and PSO for aggregator profit, energy allocation and computational efficacy. Notably, the simulation studies for 'CCA' are limited to up to seven RAs participating in the spot market due to the computational resources. Table 2 contains the coefficient values of the cost function (7) and Table 3 contains the price points transmitted to each residential agent by spot market aggregator. It is assumed that each RA submits the corresponding price-energy demand points before the next time slot. Based on the flexibility δ in (4), each house H_i submits ten different price-energy demand points that consist of $\{\pi_j - q_j^i\}$ according to the RA objective function (5). It is to be noted that the simulation results are generated using Python on a computer with Intel Core i7 (2.00 GHz) and 32GB RAM.

A. PROFIT COMPARISON

Fig. 4 shows the profit earned by the aggregator after solving the WDP using the proposed method, PSO, UPA and CCA for a fifteen minutes time slot in one specific spot market scenario. In UPA, the aggregator provided the same price

TABLE 3. **Prices from aggregator.**

Price	π_1	π_2	π_3	π_4	π_5
\$/kWh	1.14	1.12	1.0	0.9	0.85
Price	π_6	π_7	π_8	π_9	π_{10}
\$/kWh	0.8	0.7	0.6	0.5	0.4

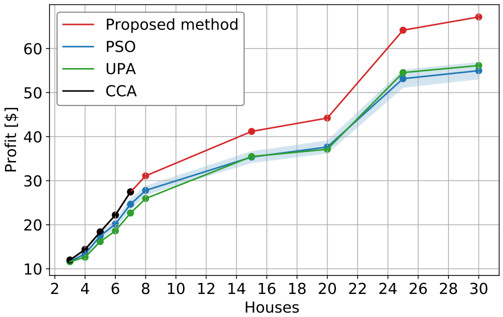

FIGURE 4. **Aggregator side profit comparison.**

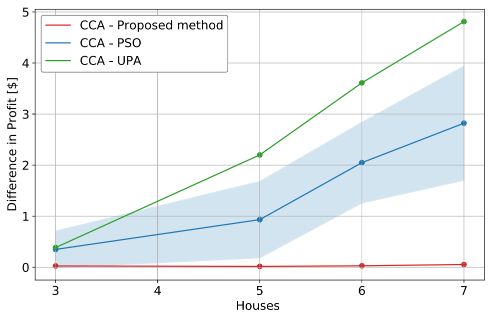

FIGURE 5. **Aggregator side profit difference compared to CCA.**

point for all the participants, corresponding to the maximum achievable profit. On the contrary, in the combinatorial auction, the aggregator provides individual energy allocation price points to each RA. That is because the aggregator evaluates the profit against all possible combinations of energy allocation and populates different price-energy allocations for each user. It is clear from Fig. 4 that combinatorial auction (CCA and the proposed method) yields the maximum profit in contrast to other techniques, which increases with an increase in the number of participating houses H_i and $i = \{1, 2, 3, .., 30\}$. However, the evaluation of CCA was carried out only up to seven houses since it requires greater computational time, which is not feasible in the real-time spot markets. Furthermore, PSO (blue colored) suffered from an envelope of the range as it is a meta-heuristic method with uncertainty in every iteration. The difference in the profits amongst the methods compared in this simulation study is also embedded in Fig. 5.

B. ENERGY ALLOCATION COMPARISON

In terms of energy allocation, Fig. 6 displays the comparison between all four methods for energy allocated to RAs participating in the spot market energy auction. The proposed method resulting from Algorithm 1 yields the best energy allocation as the number of houses increases.

Fig. 7 displays the difference in the energy allocation of three techniques with respect to the CCA. It can be observed that the UPA trajectory (green-colored) diverges, while the

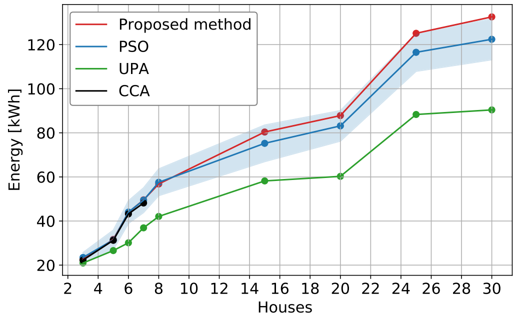

FIGURE 6. **Aggregator side energy allocation comparison.**

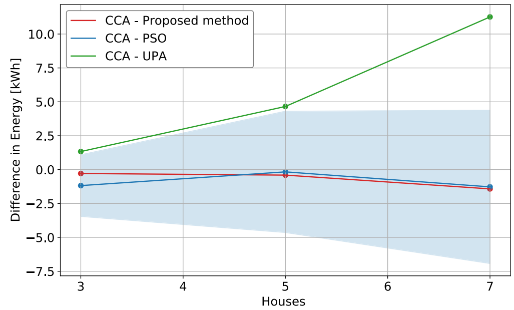

FIGURE 7. **Aggregator side energy allocation difference compared to CCA.**

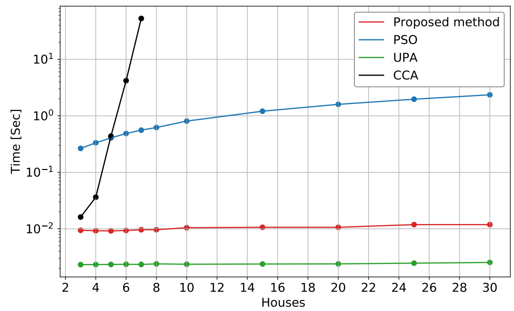

FIGURE 8. **Aggregator side computational time comparison.**

difference between the proposed method (Red-colored) and CCA is quite close to zero. Similarly, this difference is also close to zero for PSO (blue-colored). Unfortunately, the PSO method [7] despite being close to the proposed method, suffers from high variance. That leads to unreliable results in the energy allocation.

C. COMPUTATIONAL EFFICIENCY

Despite achieving higher profit and better energy allocation, the major shortcoming of the conventional combinatorial method is very high computational time that increases the computational load and becomes infeasible. From M^N, it is clear that as the number of houses N increases, the variety of possible allocation points increases exponentially. Consequently, evaluating each aggregated energy point becomes mandatory for maximum profit. This becomes impractical with a higher number of participations in the transactive energy spot market between five to fifteen minutes.

Fig. 8 depicts the computational time required by each method compared to the increasing number of houses. Surprisingly, when participants increase beyond six, CCA's computational time starts rising dramatically, which displays a poor computational algorithm. On the other hand,

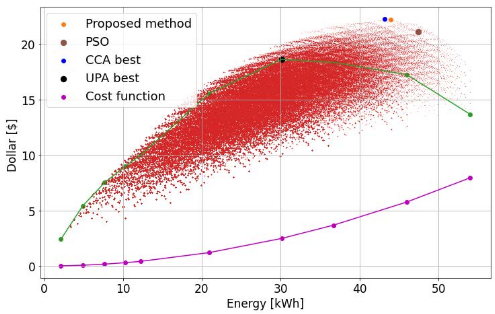

FIGURE 9. Aggregator decision process in spot market.

a reasonable computational time is clocked via the PSO algorithm, but comparatively more than the proposed algorithm and UPA.

Consider a case study of six houses H_i with $i = \{1, 2, 3, 4, 5, 6\}$ participating in the spot market. Let the number of houses N are six and the number of price points M transmitted are ten, then based on M^N there are 10^6 different possible choices for energy allocation (Fig. 9). The magenta-colored curve represents the cost function (6). While the red dots represent all the 10^6 different possible choices. The blue dot shows the global maximum profit (22.20$) point achieved through the CCA; whereas, the orange-colored dot shows the profit (22.18$) point achieved via the proposed method. Utilizing, the UPA and PSO approaches maximum profit of 18.59$ and 19.21$ was achieved as shown via black-colored and brown-colored dots, respectively.

The computational time required by the CCA for six houses was seven seconds; surprisingly, when solved for seven houses, the computational time increased drastically to one minute and twenty seconds (Fig. 8). For more than seven houses, it becomes impractical to solve because the computational time keeps on increasing with the number of houses as depicted by black-colored trend in Fig. 8. On the other hand, solving for a similar condition with the proposed Algorithm 1, the computational time was three milliseconds with optimal profit yield nearer to the CCA. Thus, the proposed method achieved superior efficacy in terms of computational time as well as in achieving maximum profit and better energy allocation for each RA in the transactive energy spot market.

V. CONCLUSION

A formal approach to solving the NP-hard problem of the winner determination process in the combinatorial single-sided auction for the transactions in the spot market is presented in this paper.

- The proposed approach exploited the multi-variable Taylor series to arrive at the personalized approximate cost function for each residential agent, reducing the search space in the spot market transaction.
- The simulation study was carried out for actual real-life house data participating in the spot market. Simulation results depict the superiority of the proposed approach to achieving substantial improvements in the computational time, earning approximately sixteen percent more profit than the uniform price auction.
- The proposed system hinges on formal methodology rather than a heuristic method. That resulted in definite energy allocation for each residential agent.

The proposed approach is a general methodology for many applications, including residential houses with flexible loads or a group of communities with thermostatically controlled loads to maximize the profit with the superior performance of the aggregator in the real-time spot market energy transactions. In future work employing the proposed method could be of substantial interest to investigate the effect of propagation from spot to day-ahead market.

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