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Market Equilibrium in Active Distribution System With μ VPPs: A Coevolutionary Approach

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ABSTRACT To further liberalize the retail electricity market, this paper establishes a novel active distribution system market (ADSM) to encourage the new entries of micro virtual power plants (μ VPPs) as prosumers. μ VPPs compete with traditional retailers by submitting price–quantity bids/offers for energy and reserve resources. The joint operation of energy and reserve market is modeled as a bilevel equilibrium problem with equilibrium constraints (EPEC) with an upper-level objective that maximizes all μ VPPs' profit and a lower level objective that maximizes social welfare of the market clearing process. A coevolutionary approach is successfully employed to determine the pure strategy Nash equilibrium of the EPEC model. The case studies demonstrate the effectiveness of the coevolutionary method and show that μ VPPs' bidding/offering strategies depend significantly on the penetration level of distributed energy resources and renewable energy sources and they can be considerably influenced by rivals' strategies. This paper then compares μ VPPs' performances under different market structures and addresses the advantages of the proposed ADSM in terms of higher asset utilization rate, higher economic profit, and more secured return on investment.

INDEX TERMS Micro virtual power plant (μ VPP), active distribution system market (ADSM), distribution system operator (DSO), bilevel EPEC, coevolutionary computation.

I. INTRODUCTION

It has been more than ten years since the UK electricity retail market was liberalized, evident barriers to entry still remain for small suppliers. It is hard for small suppliers to secure contracts of small quantity to match their load profile, for the long duration they are seeking and at a price that is competitive with the large vertically integrated suppliers [1]. Another prominent barrier is the expectation of low or even negative margins for small scale retail-only business. In contrast, the six large suppliers continue to dominate the electricity retail segments with a combined market shares of 85% [2]. However, their consumers have not experienced significant price reductions while the consumption level continues to rise from 2012 to 2016, resulting in expensive electricity bills [2]. In recent years, there is a growing trend to introduce Microgrids (MGs) and Virtual Power Plants (VPPs) as new entries into the electricity retail market and overcome the barriers mentioned above. MGs and VPPs' access to supply is guaranteed by local distributed generation, their do not share the same level of reliance on wholesale market as their vertically integrated supplier counterparts. This should

reduce losses in the transmission of wholesale electricity and potentially justify a reduction in the network charges that end-consumers pay [3]. Accordingly, the participation of MGs and VPPs will require an updated market framework in the retail segments and a more decentralized management.

Considering the small-scale generation capacity and the residential level demand, the concept of micro Virtual Power Plant (μ VPP) is proposed here to include MGs and VPPs that are connected to the restructured distribution system. μ VPP is defined as an extension to the MG concept since the distributed energy resources (DER) located within the μ VPP has a capacity that can cover either part of the load or generate excess electricity to be consumed by other μ VPPs. To optimally exploit μ VPPs' potentials, the concept of active distribution system has been brought forward by [4]–[6]. In [4], the framework of active distribution system was proposed to minimize the import of energy from the main grid. Reference [5] pointed out that the DER should not only contribute to the local energy balancing but also to the ancillary services. In addition, [6] addressed the urgent need to design a new market mechanism for the emerging active

distribution system. This paper proposes a novel active distribution system market (ADSM) that mimics the wholesale auction market under clearing pricing rule. μ VPPs and traditional retailers as market participants tender supply and demand bid curves in the format of quantity and price bids. Then Distribution System Operators (DSOs) construct aggregated hourly supply and demand curves to determine market clearing prices as well as the corresponding supply and demand schedules [7]. The benefits of implementing such an auction market in active distribution system are shared by all market participants: for μ VPP owners, the electricity generated from their DER assets now has the same market value as the electricity purchased from wholesale market [8]. μ VPP owners are expected to receive a higher return on investment than the current low feed-in tariff [9]. For DSOs, the growing entries of μ VPPs reduce the system operators' exposure to the risk associated with the unpredictability of spot market prices and volatility in consumption patterns [10]. Finally for end-consumers, they pay at cheaper electricity retail rates due to the increased competition in the restructured retail market.

Finding the equilibrium of the active distribution system market described above is crucial. DSOs use the equilibrium model to monitor and assess the market while the participants use the model to make strategic decisions on their bids and offers. Using a bilevel optimization formulation, the competition in electricity wholesale market was modeled as an equilibrium problem with equilibrium constraints (EPEC) [11]–[17]. EPEC arises when analyzing multi-leader-follower games where multiple firms compete non-cooperatively in an oligopolistic market. EPEC formulation captures the relationship between generation companies and system operators as a hierarchical relationship between two autonomous, and possibly conflictual, decision makers [18]. This description is also fitting for the proposed distribution system market: DSOs expect minimized cost for clearing the market, however, an optimal market clearing results should bring profits to μ VPPs – otherwise the μ VPP owners are deterred from entering the market and the μ VPPs become isolated MGs. Once the DSOs have cleared the market, μ VPPs react to the clearing price and quantities and refine their bidding/offering strategies such that their profits are maximized. In [11]–[13], the bilevel EPECs were reformulated as a single-level optimization problem by using Karush-Kuhn-Tucker (KKT) conditions and dual theory. Reference [11] presented a decision-making model for distribution companies with DERs in a competitive wholesale market, in which the distribution companies submitted quantity bids/offers sourced from their DERs. Reference [12] applied a more practical market setting by including the price variables in the offers. In [13], the bilevel model was implemented in active distribution system market and the economic benefits of DER aggregators were addressed, however, those aggregators were still prohibited to participate in the price-making process hence the market power of their DER generation was not analyzed.

There are two inherent disadvantages when applying the KKT conditions and dual theory in realistic electricity market: firstly this method is based on the optimistic assumption of a convex lower-level problem. Under this assumption, the “follower” (i.e. DER aggregators) altruistically submits an optimal bid/offer that also benefits the “leader” (system operators) [19]. In reality the leader can't influence the followers' decision in a non-cooperative market environment and the followers should determine bids/offers based on their own economic benefits. Secondly the reformation towards a single-level problem brings many Lagrange multipliers which make the procedure difficult for practical markets with detailed constraints [20]. In [14], an alternative method of primal-dual approach was proposed to solve the bilevel market equilibrium model under the same optimistic assumption of convex formulation. Binary expansion approach was implemented in [15] and [16] to transform nonconvex problem into mixed-integer linear problem with acceptable loss of accuracy. An iterative approximation algorithm was used in [17] as another alternative method but the results were not guaranteed to be Nash Equilibrium (NE).

Coevolutionary computation is a relatively new form of agent-based simulation approach developed from classical evolution algorithms, which adopts the notion of ecosystem where multiple species coevolve towards mutual benefit [21]. Consequently, it is very suitable for bilevel optimization problem which has a hierarchical structure between two decision-making groups. Coevolutionary computation solves the two levels sequentially, improves solutions on each level separately, while periodically exchanging information to get a good overall solution on both levels [22]. Coevolutionary computation was successfully applied in modelling bilevel wholesale market with Cournot and Supply Function Equilibrium (SFE) formulation [23]–[25]. Reference [23] addressed the advantages of coevolutionary computation as a parallel and global search algorithm. However, [24] and [25] pointed out that the coevolutionary Cournot/SFE approach may not be effective if market players have heterogeneous cost functions, which was exactly the case in active distribution system market where μ VPPs have a mix of different DERs.

This paper presents a novel ADSM framework that facilitates the trading among μ VPPs in energy and reserve retail markets. The market equilibrium problem is formulated as a bilevel EPEC where the upper-level problem aims at maximizing each μ VPP's profit and the lower-level problem maximizes the social welfare in market clearing stage. A novel coevolutionary approach is proposed in this paper to find pure strategy Nash Equilibrium (NE) of the ADSM operation. The main contributions of this paper are identified as follows:

1. An active distribution system market framework is established to better utilize the emerging μ VPPs. The potentials of their DERs are optimally exploited to contribute to energy-reserve equilibrium at retail level.
2. The joint operation of energy and reserve markets is formulated as a bilevel EPEC by combining the optimality conditions of all upper-level problems. It also

addresses the dual role of μ VPP as either “producer” or “consumer” and the heterogeneous DER assets located inside μ VPP.

3. To the best of the authors’ knowledge, it is the first paper to utilize coevolutionary approach to derive pure strategy NE in an active distribution system market. Compared with conventional methods, the proposed coevolutionary approach demonstrates its effectiveness when handling nonlinear market model and renders pure strategy NE without loss of accuracy.
4. Case studies are carried out in which μ VPPs are operated as pure MG, price-takers in passive distribution system market and price-makers in active distribution system market. The comparative study shows the economic rationale of the proposed market framework and analyzes the factors that could affect the bidding/offering strategies of μ VPPs.

This paper is organized into five sections. Section II describes the active distribution system market framework and its bilevel EPEC formulation. The coevolutionary computation approach is presented and applied to find pure strategy NE in Section III. The numerical results are displayed and analyzed in Section IV. Section V draws the conclusion.

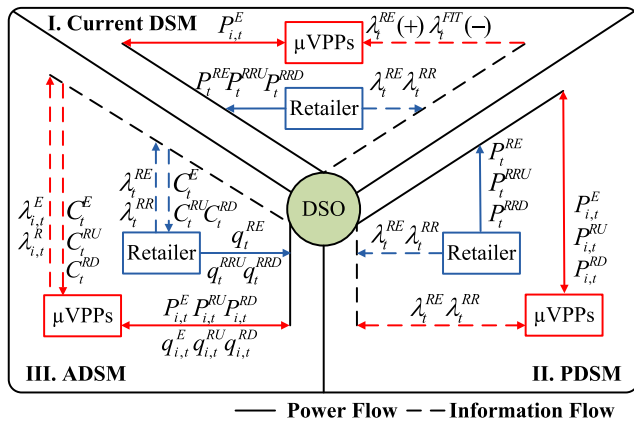


FIGURE 1. Three types of distribution system markets.

II. BILEVEL EPEC FORMULATION OF ACTIVE DISTRIBUTION SYSTEM MARKET

A. THREE MARKET FRAMEWORKS IN DISTRIBUTION SYSTEM

Fig. 1 illustrates the proposed active distribution system market (ADSM) structure. To highlight its novelties, the frameworks of the current distribution system market (DSM) and a passive distribution system market (PDSM) are also included. The participants in three types of distribution markets include μ VPPs and traditional retailers and the markets are managed by DSOs. The differences between market types lie in the role of μ VPPs, type of the bids/ Table 1 shows.

1) CURRENT DSM

The section “I. Current DSM” in Fig. 1 illustrates the power flow and the information flow between market participants and DSOs in the current electricity retail market. For an

TABLE 1. The differences between three types of distribution system markets.

Types	Role of μ VPPs	Type of Bids	Market Status
Current DSM	Consumer	N/A	Retailer-dominant
PDSM	Price-taking Prosumer	Quantity Bids/Offers	Close-to-Perfect Competition
ADSM	Price-making Prosumer	Price-Quantity Bids/Offers	Oligopolistic Competition

individual μ VPP, the DERs generate electricity only to satisfy its own demand during the periods when the operation cost is lower than retail energy price. Otherwise the μ VPP submits the quantity $P_{i,t}^E$ (kW) it intends to buy from retailers at the retail energy price λ_t^{RE} (£/kWh). The DSOs then sum up the demand from μ VPPs and request the total amount of P_t^{RE} (kW) from the retailers. There are times when renewable energy sources (RES) generate more than the demand needs, μ VPP will export the excess power back to grid at feed-in tariff λ_t^{FIT} (£/kWh). As for reserve capacities required in the distribution system, the upward reserve demand P_t^{RRU} (kW) and downward reserve demand P_t^{RRD} (kW) are completely supplied by retailers at retail reserve price λ_t^{RR} (£/kWh). To sum up, the current distribution system market is dominated by retailers. The capacities of DERs are restricted to be consumed inside μ VPPs, thus the function of μ VPPs is degraded into MGs and the role of μ VPPs is limited as pure consumers despite their insignificant renewable export.

2) PDSM

The section “II. PDSM” in Fig. 1 depicts the transaction of power and information between market participants and DSOs in a PDSM. In a PDSM, the transactions of power in energy market and reserve market are priced at retail price λ_t^{RE} and λ_t^{RR} respectively. Based on the price signals, μ VPPs submit two sets of hourly quantity bids/offers: the energy bid or offer $P_{i,t}^E$ (kW) to purchase or sell energy and the upward/downward reserve offer P_t^{RRU} / P_t^{RRD} (kW) to provide regulating service. Then DSOs clear the energy and reserve markets for each hour by matching the quantity in supply offers to the quantity in demand bids. The dual role of both producer and consumer defines μ VPPs as prosumers. As price-takers, μ VPPs and traditional retailers provide a homogeneous product at the same price which leads the market towards perfect competition. However, the volatility and small-scale capacities of DERs’ generation make μ VPPs an imperfect substitution for traditional retailers therefore the PDSM can be described as “close-to-perfect”.

3) ADSM

The proposed ADSM is shown in section “III. ADSM” in Fig. 1. μ VPPs participate in the ADSM as price-making prosumers by submitting two sets of hourly price-quantity bids/offers: the energy bid or offer $P_{i,t}^E$ (kW) at price $\lambda_{i,t}^E$ (£/kWh) to purchase or sell energy; the upward/downward reserve offer $P_{i,t}^{RU} / P_{i,t}^{RD}$ (kW) at price $\lambda_{i,t}^R$ (£/kWh). Traditional retailers, on the other hand, offer ADSM with quantities

that are large enough to cover all the energy demand and reserve demand inside the distribution system at their retail prices. Then DSOs clear the energy and reserve markets for each hour and produce the clearing price and clearing quantity for both markets aiming at maximizing social welfare. DSOs inform μ VPPs of their clearing quantity $q_{i,t}^E$ (kW) and clearing price C_t^E (£/kWh) after clearing the energy market; the clearing quantity $q_{i,t}^{RU}/q_{i,t}^{RD}$ (kW) and clearing price C_t^{RU}/C_t^{RD} (£/kWh) after clearing the upward/downward reserve market. The same clearing prices $C_t^E/C_t^{RU}/C_t^{RD}$ (£/kWh) also apply to traditional retailers for their clearing quantity $q_t^{RE}/q_t^{RRU}/q_t^{RRD}$ (kW) in the energy market, upward reserve market and downward reserve market respectively.

The market frameworks of the current DSM and PDSM are used in this paper as reference cases to demonstrate the advantages of ADSM. The maximization of μ VPPs' profit (or equally the minimization of their cost) in the current DSM and PDSM can be easily formulated as mixed-integer linear problem (MILP) and solved by commercial solvers. The results are utilized to investigate the operation strategies of μ VPPs under different market setups in Section IV. This paper concentrates on formulating the proposed ADSM equilibrium model as a bilevel EPEC. The upper-level (UL) problem aims at maximizing the economic profit of each μ VPP and the lower-level (LL) problem aims at maximizing the social welfare of the market clearing process. The objective functions and constraints of the bilevel EPEC are presented as follows:

B. μ VPP PROFIT MAXIMIZATION UL PROBLEMS

The objective function of the UL problems is formed as:

$$\max_{i \in I} \sum_{t=1}^{NT} \left\{ C_t^{RU} P_{i,t}^{RU} + C_t^{RD} P_{i,t}^{RD} - C_t^E P_{i,t}^E + C_t^E P_{i,t}^L - \left(C_i^{Gen} P_{i,t}^{Gen} + C_i^{SU} u_{i,t} + C_i^{SD} v_{i,t} \right) \right\} \quad (1)$$

where the first two terms $C_t^{RU} P_{i,t}^{RU} + C_t^{RD} P_{i,t}^{RD}$ represent the revenue received from upward and downward reserve markets. The third term $C_t^E P_{i,t}^E$ is the cost for energy bid. If μ VPP offers energy to the market, the term $-C_t^E P_{i,t}^E$ is another source of revenue. The fourth term $C_t^E P_{i,t}^L$ is the income from supplying μ VPPs' end-consumers. The income and payment of the transactions between μ VPPs and ADSM are calculated by multiplying the offering/bidding quantities by the clearing prices. The last term $C_i^{Gen} P_{i,t}^{Gen} + C_i^{SU} u_{i,t} + C_i^{SD} v_{i,t}$ is the generation cost of dispatchable generators (DG) owned by μ VPPs.

Subject to the following constraints

$$-o_{i,t-1} + o_{i,t} - o_{i,k} \leq 0, 1 \leq k - (t - 1) \leq T_{on}^{Gen} \quad \forall i, \forall t \quad (2)$$

$$o_{i,t-1} - o_{i,t} + o_{i,k} \leq 1, 1 \leq k - (t - 1) \leq T_{off}^{Gen} \quad \forall i, \forall t \quad (3)$$

$$-o_{i,t-1} + o_{i,t} - u_{i,t} \leq 0 \quad \forall i, \forall t \quad (4)$$

$$o_{i,t-1} - o_{i,t} - v_{i,t} \leq 0 \quad \forall i, \forall t \quad (5)$$

$$u_{i,t} - v_{i,t} - o_{i,t} + o_{i,t-1} = 0 \quad \forall i, \forall t \quad (6)$$

$$P_{i,t}^{Gen} \leq P_{i,t}^{Gen} o_{i,t} \leq \underline{P}_{i,t}^{Gen} \quad \forall i, \forall t \quad (7)$$

$$P_{i,t}^{Gen} - P_{i,t-1}^{Gen} \leq (2 - o_{i,t-1} - o_{i,t}) \underline{P}_{i,t}^{Gen} + (1 + o_{i,t-1} - o_{i,t}) RU_i \quad \forall i, \forall t \quad (8)$$

$$P_{i,t-1}^{Gen} - P_{i,t}^{Gen} \leq (2 - o_{i,t-1} - o_{i,t}) \underline{P}_{i,t}^{Gen} + (1 - o_{i,t-1} + o_{i,t}) RD_i \quad \forall i, \forall t \quad (9)$$

$$-EXCH_{max} \leq P_{i,t}^E \leq EXCH_{max} \quad \forall i, \forall t \quad (10)$$

$$P_{i,t}^E + P_{i,t}^{Gen} + P_{i,t}^W = P_{i,t}^L \quad \forall i, \forall t \quad (11)$$

$$0 \leq r_{i,t}^{Gen,up} \leq \omega_{up} \bar{P}_i^{Gen} \quad \forall i, \forall t \quad (12)$$

$$0 \leq r_{i,t}^{Gen,dw} \leq \omega_{dw} \bar{P}_i^{Gen} \quad \forall i, \forall t \quad (13)$$

$$P_{i,t}^{Gen} + r_{i,t}^{Gen,up} \leq \bar{P}_i^{Gen} o_{i,t} \quad \forall i, \forall t \quad (14)$$

$$P_{i,t}^{Gen} - r_{i,t}^{Gen,dw} \geq \underline{P}_i^{Gen} o_{i,t} \quad \forall i, \forall t \quad (15)$$

$$P_{i,t}^{Gen} - P_{i,t-1}^{Gen} + r_{i,t}^{Gen,up} \leq (2 - o_{i,t-1} - o_{i,t}) \underline{P}_{i,t}^{Gen} + (1 + o_{i,t-1} - o_{i,t}) RU_i \quad \forall i, \forall t \quad (16)$$

$$P_{i,t-1}^{Gen} - P_{i,t}^{Gen} + r_{i,t}^{Gen,dw} \leq (2 - o_{i,t-1} - o_{i,t}) \underline{P}_{i,t}^{Gen} + (1 - o_{i,t-1} + o_{i,t}) RD_i \quad \forall i, \forall t \quad (17)$$

$$0 \leq P_{i,t}^{RU} \leq r_{i,t}^{Gen,up} \quad \forall i, \forall t \quad (18)$$

$$0 \leq P_{i,t}^{RD} \leq r_{i,t}^{Gen,dw} \quad \forall i, \forall t \quad (19)$$

The variables involved in the UL problem include: the energy bid/offer quantity $P_{i,t}^E$ (kW) of the i th μ VPP during period t , positive value of the variable represents a bid to buy energy while negative value represents an offer to sell energy; the reserve offer quantity $P_{i,t}^{RU}/P_{i,t}^{RD}$ (kW) of the i th μ VPP during period t ; the DG power output $P_{i,t}^{Gen}$ (kW), binary operation variable $o_{i,t}$, start-up variable $u_{i,t}$, shut-down variable $v_{i,t}$ and the available capacity $r_{i,t}^{Gen,up}$ (kW)/ $r_{i,t}^{Gen,dw}$ (kW) of upward/downward spinning reserve of the i th μ VPP during period t . The constants include: the operation cost C_i^{Gen} (£/kWh), start-up cost C_i^{SU} (£/kWh) and shut-down cost C_i^{SD} (£/kWh) of the DG owned by the i th μ VPP; the transaction limit $EXCH_{max}$ (kW) between μ VPP and ADSM; the upper limit \bar{P}_i^{Gen} (kW) and the lower limit \underline{P}_i^{Gen} (kW) of the DG output power in the i th μ VPP; the minimum time T_{on}^{Gen} (h) that generator should be on and the minimum time T_{off}^{Gen} (h) it should be off per day; ramp up limit RU_i (kW/h) and ramp down limit RD_i (kW/h) that characterize the speed of providing upward or downward spinning reserve of the generator in the i th μ VPP; the percentage of ω_{up}/ω_{dw} that limits the maximum capacity of upward/downward spinning reserve with regard to generation capability.

Equation (2) and (3) are the minimum on time and minimum off time constraints for generators respectively. Equation (4) - (6) define the start-up and shut-down variables. Equation (7) ensures the power output of each generator is within its capacity. Equation (8) and (9) apply the ramping rate limits on the speed of each generator to increase or decrease its power output. Equation (10) defines the upper and lower limits of the energy bid/offer quantity.

Equation (11) is the power balance constraint between supply and demand for each μ VPP. Equation (12) and (13) set the upper limit of upward and downward spinning reserve that are available from each generator. In addition, the production of upward or downward spinning reserve capacity should also abide by the output power limit and ramping limit as indicated by (14) - (15) and (16) - (17) respectively. Equation (18) explains that the upward reserve capacity offer is originated from ramping up the generator output. Similarly, constraints (19) explains that the downward reserve offer is sourced from ramping down the generator output.

C. DSO OPERATION COST MINIMIZATION LL PROBLEM

The objective function of the LL problem is formulated as:

$$\begin{aligned} \text{Max}_{t \in T} \left\{ \sum_{i=1}^{NI} \left[\lambda_{i,t}^E q_{i,t}^E - \left(\lambda_{i,t}^R + C_{i,t}^{ULOC} \right) q_{i,t}^{RU} \right. \right. \\ \left. \left. - \left(\lambda_{i,t}^R + C_{i,t}^{DLOC} \right) q_{i,t}^{RD} \right] \right. \\ \left. - \lambda_t^{RE} q_t^{RE} - \lambda_t^{RR} \left(q_t^{RRU} + q_t^{RRD} \right) \right\} \quad (20) \end{aligned}$$

where the term $\lambda_{i,t}^E q_{i,t}^E$ stands for the consumer benefit if the i th μ VPP acts as consumer in the energy market during period t (the value of clearing quantity $q_{i,t}^E$ is positive for consumer μ VPP). If the μ VPP acts as producer, the term $-\lambda_{i,t}^E q_{i,t}^E$ represents the production cost (the value of clearing quantity $q_{i,t}^E$ is negative for producer μ VPP). The term $\left(\lambda_{i,t}^R + C_{i,t}^{ULOC} \right) q_{i,t}^{RU}$ is the production cost of the i th μ VPP in the upward reserve market, in which the marginal cost consists of the reserve offer price $\lambda_{i,t}^R$ and lost opportunity cost $C_{i,t}^{ULOC}$. Similarly, the term $\left(\lambda_{i,t}^R + C_{i,t}^{DLOC} \right) q_{i,t}^{RD}$ is the production cost of the i th μ VPP in the downward reserve market. The production costs of traditional retailer in both energy and reserve market are also included and they are calculated as $\lambda_t^{RE} q_t^{RE}$ and $\lambda_t^{RR} \left(q_t^{RRU} + q_t^{RRD} \right)$ respectively. The social welfare of the market clearing process is then derived by deducting the overall production cost from the total consumer benefit.

The LL objective function (20) subjects to the following constraints:

$$\underline{\lambda}_t^E \leq \lambda_{i,t}^E \leq \bar{\lambda}_t^E \quad \forall i, \forall t \quad (21)$$

$$\underline{\lambda}_t^R \leq \lambda_{i,t}^R \leq \bar{\lambda}_t^R \quad \forall i, \forall t \quad (22)$$

$$\begin{cases} P_{i,t}^E \leq q_{i,t}^E \leq 0, & \text{if } P_{i,t}^E < 0 \quad \forall i, \forall t \\ q_{i,t}^E = P_{i,t}^E, & \text{if } P_{i,t}^E \geq 0 \quad \forall i, \forall t \end{cases} \quad (23)$$

$$0 \leq q_{i,t}^{RU} \leq P_{i,t}^{RU} \quad \forall i, \forall t \quad (24)$$

$$0 \leq q_{i,t}^{RD} \leq P_{i,t}^{RD} \quad \forall i, \forall t \quad (25)$$

$$q_t^{RE} \geq 0, \quad q_t^{RRU} \geq 0, \quad q_t^{RRD} \geq 0 \quad \forall t \quad (26)$$

$$-q_t^{RE} + \sum_{i=1}^{NI} q_{i,t}^E = 0 \quad \forall i, \forall t \quad (27)$$

$$q_t^{RRU} + \sum_{i=1}^{NI} q_{i,t}^{RU} = \delta_{RU} \sum_{i=1}^{NI} P_{i,t}^L \quad \forall i, \forall t \quad (28)$$

$$\begin{aligned} q_t^{RRD} + \sum_{i=1}^{NI} q_{i,t}^{RD} = \delta_{RD} \sum_{i=1}^{NI} P_{i,t}^L \quad \forall i, \forall t \quad (29) \\ \begin{cases} C_{i,t}^{ULOC} = C_t^E - \lambda_{i,t}^E, & \text{if } P_{i,t}^{RU} \neq 0, \lambda_{i,t}^E < C_t^E \quad \forall i, \forall t \\ C_{i,t}^{DLOC} = \lambda_{i,t}^E - C_t^E, & \text{if } P_{i,t}^{RD} \neq 0, \lambda_{i,t}^E > C_t^E \quad \forall i, \forall t \end{cases} \quad (30) \end{aligned}$$

The variables involved in the LL problem include: the energy bid/offer price $\lambda_{i,t}^E$ (kW) of the i th μ VPP during period t ; the reserve offer price $\lambda_{i,t}^R$ (kW) of the i th μ VPP during period t ; the lost opportunity cost $C_{i,t}^{ULOC}$ (£/kWh) for upward reserve offer submitted by the i th μ VPP during period t ; the lost opportunity cost $C_{i,t}^{DLOC}$ (£/kWh) for downward reserve offer submitted by the i th μ VPP during period t ; the clearing quantity $q_{i,t}^E$ (kW) that is defined as the portion of μ VPP's energy bid/offer quantity accepted by ADSM; the clearing quantities $q_{i,t}^{RU}/q_{i,t}^{RD}$ (kW) that are defined as the portion of μ VPP's reserve offer quantities accepted by ADSM; the clearing quantity q_t^{RE} (kW) that is retailer's energy offer quantity accepted by ADSM; the clearing quantities q_t^{RRU}/q_t^{RRD} (kW) that are retailer's reserve offer quantities accepted by ADSM. The constants include: the retail energy price λ_t^{RE} (£/kWh) and retail reserve price λ_t^{RR} (£/kWh); the upper limit $\bar{\lambda}_t^E$ (£) and the lower limit $\underline{\lambda}_t^E$ (£) of the energy bid price during period t ; the upper limit $\bar{\lambda}_t^R$ (£) and the lower limit $\underline{\lambda}_t^R$ (£) of the reserve bid price during period t ; the percentage of δ_{RU}/δ_{RD} which defines the required upward and downward reserve capacities with regards to the total demand of all μ VPPs during period t .

As for constraints, equation (21) - (22) defines the upper and lower limits of the bid/offer prices in the energy market and reserve market respectively. Equation (23) describes the relationship between clearing quantity and bid/offer quantity for the i th μ VPP in the energy market: if the μ VPP acts as energy producer during period t , it is possible that its offer quantity will be not accepted, partially accepted or fully accepted. If the μ VPP acts as energy consumer during period t , then its bid quantity will be fully satisfied under any condition. The same rules apply for the reserve offer quantities submitted by the i th μ VPP during period t as equation (24)-(25) indicate. If the energy and reserve capacities produced by μ VPPs can't meet the demand, the rest will be provided by traditional retailers as equation (26) - (29) describe. The concept of lost opportunity cost is included in equality constraint (30). It is defined as the difference in net compensation for μ VPPs between what their DERs receive when providing regulation services and what the DERs would have received for providing energy only [26]. For those μ VPPs who decide to reserve some of their capacities for upward regulation service during the period when energy market clearing price C_t^E (£/kWh) is higher than the energy offer price $\lambda_{i,t}^E$ (£), they would have received an added revenue at price $C_{i,t}^{ULOC}$ (£/kWh) if the reserved capacities were sold as energy offers. Similarly, if the energy market clearing price C_t^E (£/kWh) is lower than the energy offer price $\lambda_{i,t}^E$ (£) and the μ VPPs' output is still raised uneconomically to provide

downward regulation, they should receive compensation at price $C_{i,t}^{DLOC}$ (£/kWh) for the extra energy output that will not bring any profit given the low market clearing price.

The bilevel EPEC formulation above demonstrates a highly-coupled nature of the decision-making process for both market participants and DSOs: In UL problem, μ VPPs derive their optimal bidding/offering strategies and schedule their DERs' generation based on the maximization of individual profit, in which the quantities of energy/reserve transactions are priced at the clearing prices determined in LL problem. In LL problem, DSOs derive the clearing prices and quantities based on the maximization of social welfare, in which the clearing quantities of energy/reserve transactions are priced at the original bid/offer prices from UL problem. The highly-coupled nature requires the UL problem and LL problem to be solved simultaneously. However, due to the pessimistic assumption that μ VPPs do not have any knowledge of the acceptance for their bids/offers, it is hard to utilize KKT conditions and transform the bilevel EPEC problem into a single-level problem [27]. To solve this conundrum, a novel coevolutionary approach is proposed in the next section.

III. FINDING EQUILIBRIUM OF BILEVEL EPEC USING A COEVOLUTIONARY APPROACH

To solve the bilevel EPEC formulated in Section II, this paper proposes a bilevel coevolutionary algorithm with real-coded Genetic Algorithm (GA) Operators including selection, crossover and mutation. Under the coevolutionary framework, a μ VPP is represented by a "species" i in the ecosystem and the total number of species NI corresponds to the total number of μ VPPs participating in ADSM. The "individual" of the species i is defined as the operation strategy set $\left\{ \lambda_{i,t}^E, \lambda_{i,t}^R, P_{i,t}^E, P_{i,t}^{RU}, P_{i,t}^{RD}, P_{i,t}^{Gen}, o_{i,t}, u_{i,t}, v_{i,t}, r_{i,t}^{Gen,up}, r_{i,t}^{Gen,dw} \right\}$ of the i th μ VPP for a scheduling period of 24 hours. For species i in the k th iteration, there are NS number of individuals $Ind_{k,s}^i$ which constitute a "population" Pop_k^i . The UL and LL objective functions are utilized as two separate fitness functions to assess the quality of the operation strategy set represented by individuals $Ind_{k,s}^i$. While the UL fitness function determines the fittest individual that brings the maximum profit for species i among the entire population, the LL fitness function provides a shared domain for all species to interact with one another. After NK number of iterations, the coevolutionary algorithm aims at finding the pure strategy NE set $\left(Ind_{k,s}^i \right)^*$, $\forall i$ for all species. The pure strategy NE satisfy the following conditions:

$$f_i^{UL} \left(\left(Ind_{k,s}^i \right)^* \right) \geq f_i^{UL} \left(Ind_{k,s}^i \right) \quad \forall i \quad (31)$$

$$f^{LL} \left(\left(Ind_{k,s}^i \right)^* \mid \left(Ind_{k,s}^{-i} \right)^* \right) \geq f^{LL} \left(Ind_{k,s}^i \mid \left(Ind_{k,s}^{-i} \right)^* \right) \quad \forall i \quad (32)$$

For all species i inside the ecosystem, condition (31) describes the UL optimality of the pure strategy NE set $\left(Ind_{k,s}^i \right)^*$, $\forall i$. It is the fittest individual among the entire

population that brings the maximum profit. Condition (32) states the LL optimality of the pure strategy NE: if the rest of the species $-i$ find their UL optimal strategy set $\left(Ind_{k,s}^{-i} \right)^*$, $\forall -i$, the pure strategy NE $\left(Ind_{k,s}^i \right)^*$, $\forall i$ is the best response for species i . No single μ VPP can obtain a higher margin by deviating unilaterally from its pure strategy NE profile without decreasing the social welfare of the ADSM.

A. BUILDING BLOCKS OF THE COEVOLUTIONARY ALGORITHM

1) INITIALIZATION

At the beginning of the iterative process, all elements in the individual strategy string $Ind_{0,s}^i$ are initialized with their real value to form the initial population Pop_0^i . The randomly generated value should comply with its upper and lower limits defined in constraints (2) - (19) and (21) - (22). Firstly, the binary variables $o_{i,t}, u_{i,t}, v_{i,t}$ are initialized subject to constraints (2) - (6). Based on the derived operation variable $o_{i,t}$ and constraints (7) - (9), the DG output $P_{i,t}^{Gen}$ is initialized. Then the value of energy bid/offer quantity $P_{i,t}^E$ can be derived based on constraints (10) - (11). After $P_{i,t}^{Gen}$ is settled, constraints (12) - (17) and (18) - (19) initialize the value of available reserve capacities $r_{i,t}^{Gen,up} / r_{i,t}^{Gen,dw}$ and reserve offer quantities $P_{i,t}^{RU} / P_{i,t}^{RD}$ respectively. Finally, the bid/offer prices for energy $\lambda_{i,t}^E$ and for reserve $\lambda_{i,t}^R$ are initialized based on constraints (21) - (22).

2) SELECTION

The aim of selection in the coevolution paradigm is to form a mating pool of individuals for reproduction. Fitter individuals have a higher chance to pass on their profile to the succeeding iteration and the offspring will in turn have even higher fitness. The proposed coevolutionary algorithm uses an elitism-based tournament selection method in which some of the fittest individuals could transfer their unaltered profile to their offspring [28]. In addition to the computationally efficient tournament selection method, elitism concept is applied in this paper to improve the performance of the algorithm by preventing loss of good solutions. To select fitter individuals for species i , firstly the rest of the species $-i$ must choose their best individual set $\left(Ind_{k,s}^{-i} \right)^*$, $\forall -i$ based on UL optimality. Then the individual $Ind_{k,s}^i$ from current population Pop_k^i can be evaluated with LL optimality as criterion. The elite individuals of species i are those with high LL fitness value, in other words, they represent the best response of the i th μ VPP given the strategies of the others. The selection process will then run several "tournaments" among the non-elite individuals, after which the non-elites with low LL fitness value are removed from the mating pool.

3) Crossover

For the selected individuals in the mating pool, crossover operation randomly chooses a position and the parts of two parent individuals at the position are exchanged to form

two offspring. In the proposed coevolutionary algorithm, every individual has 24 points in its strategy string which corresponds to the scheduling horizon of 24 hours. A multi-point crossover scheme is applied in this paper which means every hour is a potential point for crossover to take place. When crossover happens at hour t , all elements included in the strategy string $\left\{ \lambda_{i,t}^E, \lambda_{i,t}^R, P_{i,t}^E, P_{i,t}^{RU}, P_{i,t}^{RD}, P_{i,t}^{Gen}, O_{i,t}, u_{i,t}, v_{i,t}, r_{i,t}^{Gen,up}, r_{i,t}^{Gen,dw} \right\}$ of both parents will be exchanged. However, the crossover operation may be disruptive to the parents' genetic profile because the new strategy string at hour t may conflict with the original strings at hour $t - 1$ and $t + 1$. Therefore, the crossover operation should be supervised by constraints (2) - (19).

4) MUTATION

After crossover operation updates the individuals in the mating pool, there is a small probability for the algorithm to perform mutation operation on updated individuals. This GA operator will randomly choose a position of the individual and change the value of the string to another value within its feasible region. The probability of mutation is small but the operation itself is indispensable because it helps the search evade local optimums and prevents premature convergence [29]. When mutation happens at hour t , an element will be chosen randomly from the strategy string $\left\{ \lambda_{i,t}^E, \lambda_{i,t}^R, P_{i,t}^E, P_{i,t}^{RU}, P_{i,t}^{RD}, P_{i,t}^{Gen}, O_{i,t}, u_{i,t}, v_{i,t}, r_{i,t}^{Gen,up}, r_{i,t}^{Gen,dw} \right\}$ and changed to another feasible value. Similarly, the mutation process should also be supervised by constraints (2) - (19).

5) ENERGY AND RESERVE MARKET CLEARING

The process of energy and reserve market clearing determines the market clearing price, at which the transactions of energy/reserve capacities are priced; and the market clearing quantities, which are assigned to producers to dispatch their generation resources. The offers from suppliers including producer μ VPPs and retailers are aggregated as a monotonically increasing supply curve and the bids from consumer μ VPPs are aggregated as a monotonically decreasing demand curve. At each hour, the energy market is cleared first by finding the intersection of supply and demand curves. The price at the intersection is defined as energy market clearing price C_t^E . Then the lost opportunity cost $C_{i,t}^{ULOC} / C_{i,t}^{DLOC}$ are obtained based on equations (30). By matching the supply quantity to the demand quantity as constraints (23) and (27) suggest, the market clearing quantities $q_{i,t}^E / q_{i,t}^{RE}$ are derived for μ VPPs and retailers respectively. The DSO then clears the reserve market following the same procedure and derive the following results: reserve market clearing prices C_t^{RU} / C_t^{RD} , market clearing quantities $q_{i,t}^{RU} / q_{i,t}^{RD}$ for μ VPPs and q_t^{RRU} / q_t^{RRD} for retailers. The market clearing process represents the LL problem and the maximal social welfare is achieved at the intersection of supply and demand curves. The results obtained in this algorithmic block facilitate the calculation of LL fitness value.

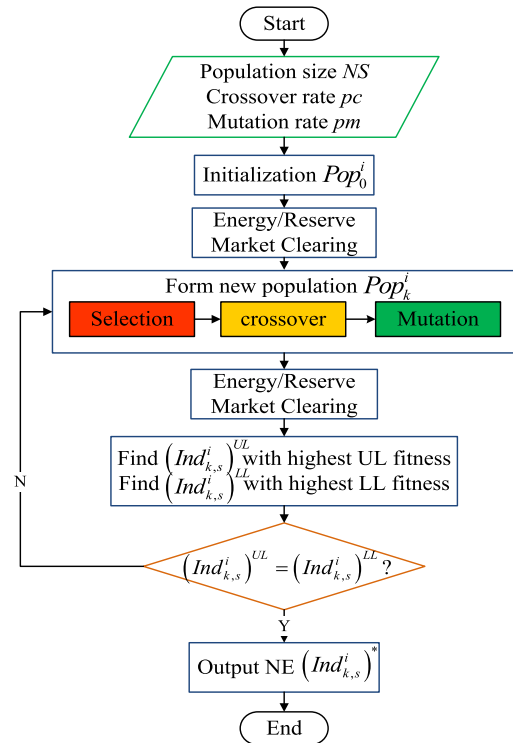


FIGURE 2. Coevolutionary algorithm workflow.

B. PROCEDURE OF THE COEVOLUTIONARY ALGORITHM

The workflow of coevolutionary algorithm in this paper is shown in Fig. 2. Detailed procedure is described as follows:

- Step 1) Initialize the first population for each species i . There are NI number of populations and each population Pop_k^i contains NS number of individuals;
- Step 2) Perform energy/reserve market clearing, obtain UL and LL fitness value of the individuals in the first population;
- Step 3) Based on the UL and LL fitness value of the individuals in the previous iteration, perform selection, crossover and mutation to form new population Pop_k^i ;
- Step 4) Perform energy/reserve market clearing, obtain UL and LL fitness value of the individuals in the current population;
- Step 5) For each species i , compare the individual $(Ind_{k,s}^i)^{UL}$ with the highest UL fitness and the individual $(Ind_{k,s}^i)^{LL}$ with the highest LL fitness;
- Step 6) Repeat Step 3) to Step 5) until $(Ind_{k,s}^i)^{UL} = (Ind_{k,s}^i)^{LL}$ is achieved for every species simultaneously, output pure strategy $NE (Ind_{k,s}^i)^*$, $\forall i$.

IV. COMPARATIVE PERFORMANCE STUDY

In the comparative performance study, the effectiveness of the proposed coevolutionary approach in finding the equilibrium

is investigated and demonstrated. Also, the operation behaviors of a single μ VPP under different market structures are analyzed, addressing the advantages of the proposed ADSM over the current DSM and PDSM. The UK retail energy price and reserve price are extracted from Nord Pool price data 2016 [30]. A modified IEEE 33 bus distribution system is used and the supply and demand nodes of the example system are aggregated into four μ VPPs to form the oligopolistic ADSM. μ VPP1 has an average hourly demand of 930kW and DER capacity of 930kW, of which RES capacity accounts for 70% of the DER capacity. μ VPP2 has a similar hourly demand of 860kW and DER capacity of 860kW, but its RES capacity accounts for only 30% of the DER. μ VPP3 has the highest hourly demand of 1445kW, the highest RES capacity of 1500kW and the highest DG capacity of 1500kW. μ VPP4 has a small demand level of 360kW and no DER assets. By assigning different profiles to the participating μ VPPs, this paper studies the impact on μ VPPs' bidding strategies brought by DER and RES penetration level.

For the parameters of the coevolutionary approach, the population size, crossover rate and mutation rate are set as 60, 0.8 and 0.1 respectively. The high crossover rate is chosen to give more genetic diversity within the population, promoting the search for new feasible solutions. The low mutation rate prevents the coevolutionary process from degrading to random search and improve the computation efficiency [29]. The operation problems in the current DSM and PDSM are formulated as MILP and solved using commercial solver CPLEX 12.1.4. The proposed coevolutionary algorithm for ADSM is coded in MATLAB and solved using embedded solvers. The equilibrium of ADSM is found after executing 253 coevolutionary iterations for 14 hours, however, the proposed method delivers pure strategy NE without loss of accuracy.

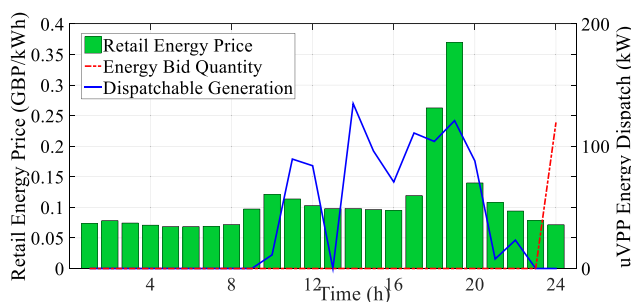


FIGURE 3. Operation strategy of μ VPP in current DSM.

A. CASE A – CONSUMER μ VPP IN CURRENT DSM

Under the market structure of the current DSM, an optimal energy dispatch is performed for μ VPP3. Its operation strategy is depicted in Fig. 3.

As shown in Fig. 3, μ VPP3 submits nearly no energy bid to the market. This μ VPP is operated autonomously from the grid due to its large DER capacity and it is indeed degraded to a MG. During the period of 9 a.m. to 23 p.m., the demand

inside μ VPP3 is satisfied by the combined output of RES and DG since the generation cost is lower than the retail energy price. However, the peak output power of DG barely exceeds 125kW compared with the rated value of 1500kW, showing a poor utilization of the DER capacity. This is because DER generation is restricted to be consumed inside μ VPP under the current DSM instead of exported for extra revenue.

B. CASE B – PRICE-TAKING PROSUMER μ VPP IN PDSM

Under the market structure of PDSM, μ VPP is permitted to submit quantity bids/offers to the market for revenue. However, they do not participate in settling the clearing prices of both energy and reserve markets. The bidding/offering strategy of μ VPP3 in PDSM is shown in Fig. 4.

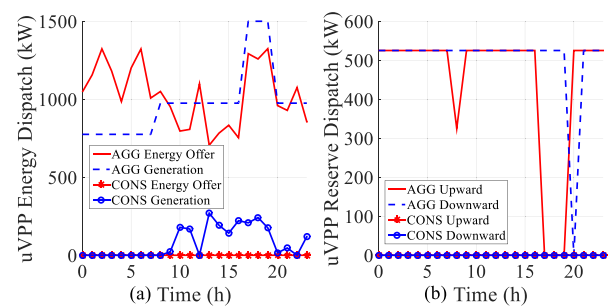


FIGURE 4. Offering strategy of μ VPP in PDSM: (a) energy market; (b) reserve market.

As a price-taker, one market player (μ VPP or retailer) has no strategic advantage over the others because they provide a homogenous product. For DSO, it makes no difference to accept the offer from a μ VPP or from a traditional retailer. Consequently, the offering strategy of a producer μ VPP can be characterized as “aggressive” (AGG) or “conservative” (CONS). In Fig. 4(a), μ VPP3 can submit aggressive energy offers to the market by keeping its DG running all day, hoping for the acceptance of all the submitted quantities and high profit. Alternatively, μ VPP3 operates conservatively and submits no energy offers. The DG is utilized only for the demand inside μ VPP3 thus the operation cost can be reduced to minimum. Fig. 4(b) demonstrates similar behaviors in the reserve market: aggressive μ VPP would use the ramping capability of its DG to make upward and downward reserve offers to the market while conservative μ VPP would offer nothing. In a non-cooperative PDSM environment, price-taking prosumer μ VPPs have a hard time determining their optimal offering strategies because they lack the market power to influence the market outcome. Consequently, their revenue from the market would vary significantly from the anticipation.

C. CASE C – PRICE-MAKING μ VPP IN ADSM

Under the framework of ADSM, μ VPPs are permitted to submit price-quantity bids/offers to the markets. The proposed coevolutionary approach achieves pure strategy NE for all participants in the market. No single μ VPP can obtain a

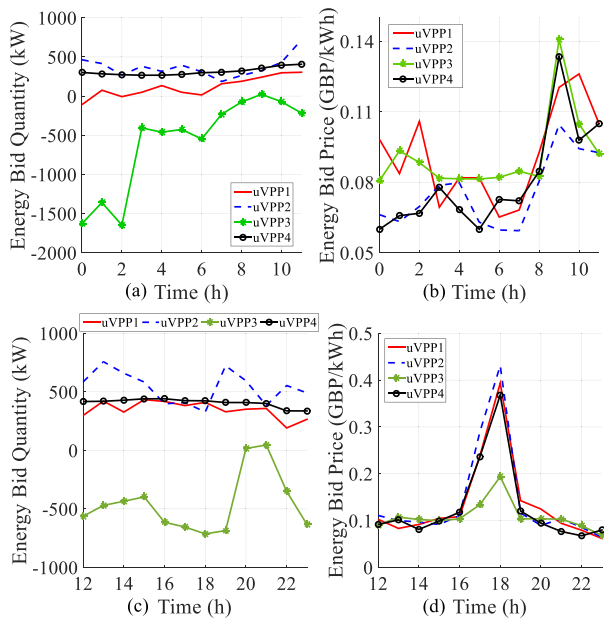


FIGURE 5. Energy bid/offer strategies in ADSM: (a) bid quantity a.m.; (b) bid price a.m.; (c) bid quantity p.m.; (d) bid price p.m.

higher margin by deviating unilaterally from its pure strategy NE profile without decreasing the social welfare of the ADSM. Their bidding/offering behaviors in the energy market are depicted in Fig. 5.

μ VPPs' behaviors in terms of bid price are analyzed based on their bid quantities. μ VPP1 and μ VPP2 have similar DER capacity and they both act as energy consumers for the first half of the day as Fig. 5(a) indicates. However, μ VPP2 has a larger percentage of DG capacity in its DER which results in lesser dependence on the imported energy. Therefore Fig. 5(b) shows that μ VPP2 tends to bid a lower price for its energy import compared with μ VPP1 knowing it can always produce its own energy even the bid is rejected. μ VPP3 acts as a pure producer in the ADSM to compete with traditional retailers. To gain strategic advantage, Fig. 5(b) shows high bid price at 9 a.m. when μ VPP3 exports low volume and low bid price during 0 a.m. to 8 a.m. when it exports high volume. μ VPP4 is a pure consumer in the ADSM and has similar load level with μ VPP2 as Fig. 5(a) shows. However, the lack of self-generation assets forces μ VPP4 to bid a higher price than μ VPP2 as Fig. 5(b) depicts. Fig. 5(c) and Fig. 5(d) describe the energy bidding/offering behaviors for the second half of the day. A peak point of energy bid price trajectories is spotted at 18 p.m. in Fig. 5(d) and it can be explained from the viewpoint of energy market clearing process. At 18 p.m., the aggregated demand of μ VPP1, μ VPP2 and μ VPP4 exceeds the supply quantity offered by μ VPP3. In this case, traditional retailers have to supply some or all of the demand at its peak retail price £0.37. For consumer μ VPPs, they tend to submit higher bid price to guarantee the acceptance of their demand bids; for producer μ VPP3, it needs to submit a lower bid price £0.2 to occupy some of the supplier market share. For DSO who aims at maximizing social welfare,

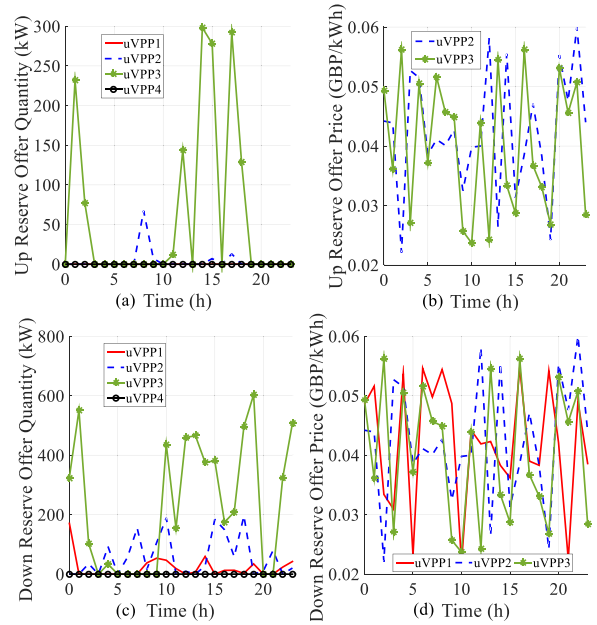


FIGURE 6. Reserve offer strategies in ADSM: (a) upward offer quantity; (b) upward offer price; (c) downward offer quantity; (d) downward offer price.

TABLE 2. Impact of market structures on μ VPP3'S operation.

Framework \ Result	Current DSM	PDSM	ADSM
DG utilization (%)	5%	5% - 65%	31%
Energy market income (£)	114.36	114.36 - 2800.86	1360.75
Reserve market income (£)	0	0 - 12508	282.33
End-user income (£)	4012.9	4012.9	3960.7
DG cost (£)	390.53	390.53 - 1955	1339.4
Total profit (£)	3736.73	3736.73 - 17366.76	4264.38

the bidding/offering strategies at 18 p.m. produce the highest consumer benefit and the lowest production cost. To sum up, the bidding/offering strategies obtained by the coevolutionary approach have achieved UL and LL optimality simultaneously.

Fig. 6(a) and Fig. 6(b) display μ VPPs' offering strategies of upward reserve capacity while Fig. 6(c) and Fig. 6(d) show μ VPPs' offering strategies of downward reserve capacity. For upward reserve market, only μ VPP2 and μ VPP3 have the DG large enough to provide upward ramping resources. Their bid prices in Fig. 6(b) follow the economic rationale to compete with traditional retailers: bid high price when the reserve production is low and bid low price when the reserve production is high. The same rule applies to determining the downward reserve offer price shown in Fig. 6(d) as μ VPP1-3 offer different volumes of downward reserve based on their DG capacities.

To address the advantage of deploying an ADSM in the distribution system, the impact of different market structures on μ VPP operation is demonstrated in Table 2. Six criteria are used to characterize μ VPP3 in the current DSM, PDSM

and the proposed ADSM respectively: DG utilization rate is calculated as the ratio of the average DG output power over its rated power; Energy market income is the revenue received from μ VPP's energy offers which are settled at market clearing price; Reserve market income is the revenue received from μ VPP's reserve offers which are settled at market clearing price; End-user income represents the payment received from μ VPP's end-consumers for energy consumption; DG cost calculates the operation cost of μ VPP's self-generation assets; finally total profit is the net revenue of μ VPP from market activities. Under the current DSM structure, consumer μ VPP only receives an insignificant payment for exporting its excessive RES generation back to grid at feed-in tariff. The DER assets within μ VPP are utilized poorly and their capacities are not exploited to generate extra revenue. The PDSM structure shows a promising DG utilization rate and a profit that is four times higher. However, these improvements are based on an optimistic anticipation that all the aggressive offers will be accepted by DSO. As price-takers, μ VPP under PDSM has no market power to influence the market clearing result thus its actual profit may deviate considerably from the anticipation. The market structure of PDSM is impractical for μ VPP to make a reliable decision. On the other hand, the framework of ADSM gives μ VPP market power to obtain reliable bidding/offering strategies that lead to secured net profit. Compared with the current DSM, μ VPP3's offering strategy at the NE point shows a good DG utilization rate of 31% and a considerable 14% increase in the total profit. Above all, the projected return on investment will be delivered as promised.

V. CONCLUSION

This paper has established a novel active distribution system market (ADSM) which allows μ VPPs to submit price-quantity bids/offers of both energy and reserve resources. Market power is granted to the DER assets by involving their owners in the price-making process of the retail market. A bilevel EPEC formulation has been presented to model the operation of both energy and reserve market at the distribution level, addressing the maximization of all μ VPPs' profit and the maximization of social welfare at the same time. A coevolutionary approach has been successfully applied for the first time to derive the pure strategy Nash Equilibrium (NE) of a non-cooperative game under the market framework of ADSM. It has been demonstrated that the proposed coevolutionary method is effective when handling nonlinear equilibrium problems with detailed market parameters.

Comparative case studies have been carried out to investigate μ VPPs' operation strategies under the market frameworks of the current DSM, PDSM and ADSM. In ADSM, simulation results have shown that the bidding/offering strategies obtained at the pure strategy NE point have achieved optimality for both upper-level problem and lower-level problem. Also, the configuration of μ VPPs in terms of their DER capacity and RES capacity has been proved to be a major factor that influences the strategic bidding/offering behaviors.

Last but not the least, the proposed ADSM has been demonstrated as a practical and economically sound framework. Simulation results have pointed out that the behaviors of μ VPPs in energy and reserve market, even for those with the same DER/RES capacities, can be significantly different from one another. Compared with the current DSM, the deployment of ADSM can better exploit the DER assets and generate higher returns on investment. Compared with PDSM, the framework of ADSM provides a secured anticipation of the profit and can better guide μ VPP owners to make bidding/offering decisions.

The proposed market framework - ADSM can accommodate the emerging μ VPPs in the current distribution system. By introducing them as new entries to the local energy and reserve markets, the retail segments of electricity will be further liberalized and ultimately end-consumers will benefit from a diversified electricity supply. The proposed EPEC formulation and its coevolutionary solution provide valuable guidance for μ VPP owners to gain strategic advantages in the upcoming retail competition. In addition, the proposed EPEC formulation and its coevolutionary solution can help DSOs to monitor and assess the market behavior.

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