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RESEARCH ARTICLE

Transactive Energy System for Distribution Network Management: Procuring Residential Flexibility Services Under Dynamic Pricing

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ABSTRACT The formulation of dynamic pricing is one of the emerging solutions to guide residential demand for the benefits of the bulk power system. However, the schedule of residential demand in response to time-differentiated energy prices could cause congestions in distribution networks at both the lowest-price and highest-price time intervals. To enable the adoption of dynamic pricing, this work presents a novel framework to manage the constraints of distribution networks based on the concept of Transactive Energy System (TES). The TES-based framework produces incentives during network issues to unlock customers' flexibility services to reschedule controllable assets (e.g., batteries). By running Home Energy Management Systems (HEMS), the flexibility of customers to modify schedules are quantified against predefined set of incentives. For each incentive, the amounts of net-demand change per customer are aggregated and submitted through aggregators to the Distribution System Operator (DSO) in the forms of both generation offers (reducing demand) and demand offers (increasing demand). The latter are crucial to cater for generation-driven network issues. The resulting aggregators' staircase bidding curves are embedded to an advanced Optimal Power Flow (OPF) model to identify the successful offers to manage network constraints whilst minimizing incentives paid to aggregators. This allows defining incentives and quantities directly without extensive iterations between DSO and aggregators. The application of the framework to an urban 11kV feeder shows its effectiveness to manage congestions. Further, the highly variations in dynamic prices increase the amounts of incentives particularly when flexibility services are requested at evening and night time intervals.

INDEX TERMS Aggregators, dynamic pricing, flexibility, home energy management systems, network management system, transactive energy system.

I. INTRODUCTION

The transition towards advanced residential electricity pricing schemes plays an important role to support the operation of power systems particularly with the wide-scale adoption of residential low-carbon technologies [1], [2], [3]. In particular, the formulation of residential time-differentiated pricing instead of the traditional flat retail tariff is considered as one of the potential emerging solutions to guide power consumption of residential customers for the benefits of power system operators [4]. This dynamic pricing scheme may also support the uptake of residential batteries and Home Energy Management Systems (HEMS) to reduce customers' electricity payments [5]. However, the management of residential demand in response to a dynamic price signals defined by the System Operator (SO) may lead to adverse technical impacts on local distribution networks [6]. Most of customers' power consumption could be scheduled towards the lowest-price time intervals to reduce electricity bills. Thus, the diversity of load will be affected resulting in new local peak demand [7]. During the highest-price time intervals, reverse power flows could also be created when residential customers maximize

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energy export to increase revenues. Therefore, the adoption of residential dynamic pricing may overload distribution networks (lines and transformers) and/or cause voltage issues [8].

To limit the aforementioned technical impacts on distribution networks, it is important that Distribution System Operators (DSOs) enhance their new roles to manage transactions of power flows across congested networks [9], [10]. Future distribution network management systems could be empowered based on the concept of Transactive Energy System (TES) to manage local energy exchanges to alleviate network issues. In this respect, incentive-based price signals could be defined to procure flexibility from residential customers to reschedule their flexible controllable assets (e.g., batteries) for the benefits of distribution networks [11]. The resulting incentives combined with dynamic prices can enable managing network constraints.

The implementation of TES in practice requires the existence of aggregators to unlock the potential flexibility from the grid-edge to submit offers to DSOs [12]. Like the wholesale electricity markets, DSOs could receive a set of offers from aggregators to either reduce or increase the aggregate net-demand of a group of individual customers to solve network issues [13], [14], [15]. Each offer determines the amount of net-demand change and the corresponding price. This in turn requires developing advanced TES-based decision-making algorithms to define feasible offers to solve network issues with the minimum amounts of incentives.

In the literature, different TES models have been proposed to minimize the electricity payments of a community with multiple individual customers in response to day-ahead energy market prices [16], [17], [18], [19], [20]. To support the operation of power system (e.g., reducing peak demand, supporting balancing mechanisms), the energy transactions are managed in real time. For this purpose, the studies in [16] and [17] combined the market prices with an adequate incentive to encourage customers rescheduling their controllable elements. However, the adopted algorithms produced the same amount of incentives for all customers without taking into account their contributions in reducing electricity payments. This in turn might cause unnecessary increase in the total amount of incentives paid to customers. Further, the role of customers and aggregators in [16] and [17] were limited to the response to the price signals. To minimize incentives, advanced bid-based TES models are proposed in [18], [19], and [20]. Each submitted bid includes the quantities of net-demand change and the corresponding price. Within these models, the incentives were provided according to customers' offers and flexibility to modify their initial net-demand schedules. However, the formulations did not cater for network constraints.

Advanced TES models were proposed in [21], [22], [23], [24], [25], [26], [27], [28], [29], and [30] to cater for the constraints of distribution networks. This was done either by the definition of power thresholds to the aggregate net-demand [21], [22], [23], [24], [25] or by using Optimal Power Flow (OPF) [26], [27], [28], [29], [30] as the decision-making algorithm. For instance, the price-based OPF presented in [26] aims to solve congestions through the provision of incentive signals to customers in return of controlling their power consumption for the benefits of distribution networks. The above studies assumed that DSOs/aggregators have the ability to directly control customers' assets to solve network issues. This might not be implementable in practice. The aggregators may not have access to the full data of distribution networks to manage network constraints. In contrast, DSOs with unbundling regulation rules do not have direct link with customers' meters. Further, the adoption of OPF to manage large numbers of controllable variables may significantly increase the computational burden of the optimization engine. Thus, the scalability of the TES algorithm will be limited.

A few models in the literature realistically model the interactions between customers, aggregators and DSOs [27], [28], [29], [30]. Although iterative optimization-based approaches were adopted to define the successful bids, extensive iterations between the DSO and aggregators were required to agree on quantities and prices. Furthermore, the proposed algorithms are limited to solve demand-driven network issues (at the low-price). All the previous mentioned studies do not cater for network issues resulting from reverse power flows when energy export of residential customers is increased to sell energy at high prices.

Based on the above, Table 1 provides a summary of the gaps in the literature. To bridge the gaps from previous studies, this work presents a framework to manage the constraints of distribution networks under residential dynamic energy pricing using the concept of transactive energy system. The TES-based framework produces incentive-based price signals during network issues to procure flexibility from residential customers to reschedule their controllable assets. By running HEMS, the maximum flexibility to modify schedules are assessed per residential customer against the predefined set of incentives. The resulting amounts of potential net-demand changes are aggregated and submitted through aggregators to the DSO in the form of generation offers (reducing demand) and demand offers (increasing demand). Each offer determines the quantity of potential net-demand change and the corresponding price. The successful offers are identified using an optimal power flow model formulated to minimize the allocated incentives to aggregators (in return of net-demand adjustment) whilst respecting network constraints.

The contributions of this work compared to previous studies could be summarized via the following bullet points:

- The TES-based framework caters for both congestions and voltage issues resulting from the response of residential customers to dynamic price signals.
- The framework deals with network issues due to the loss of diversity of load at both the lowest-price (demand-driven network issues) and highest-price time intervals (generation-driven network issues). This provides improvement from previous studies that are limited to demand-driven network issues.

TABLE 1. Features of TES in the literature-comparisons.

<table>
<tr><th colspan="2" rowspan="2">TES framework</th><th colspan="6">Studies in the literature</th><th rowspan="2">This work</th></tr>
<tr><th>[16, 17]</th><th>[18-20]</th><th>[21-25]</th><th>[26]</th><th>[27-29]</th><th>[30]</th></tr>
<tr><td rowspan="3">Participants in the TES framework</td><td>DSO</td><td>No</td><td>No</td><td>Yes</td><td>Yes</td><td>Yes</td><td>Yes</td><td>Yes</td></tr>
<tr><td>Aggregators</td><td>Yes</td><td>Yes</td><td>Yes</td><td>No</td><td>Yes</td><td>Yes</td><td>Yes</td></tr>
<tr><td>Customers</td><td>Yes</td><td>Yes</td><td>Yes</td><td>No</td><td>Yes</td><td>Yes</td><td>Yes</td></tr>
<tr><td rowspan="2">Role of customers and aggregators</td><td>Responding to price signals</td><td>Yes</td><td>Yes</td><td>Yes</td><td>No</td><td>Yes</td><td>Yes</td><td>Yes</td></tr>
<tr><td>Provision of flexibility offers</td><td>No</td><td>Yes</td><td>Yes</td><td>No</td><td>No</td><td>Yes</td><td>Yes</td></tr>
<tr><td rowspan="2">Residential flexibility offers</td><td>Quantification of flexibility</td><td>Yes</td><td>Yes</td><td>Yes</td><td>No</td><td>Yes</td><td>Yes</td><td>Yes</td></tr>
<tr><td>Pricing of flexibility</td><td>No</td><td>Yes</td><td>Yes</td><td>No</td><td>No</td><td>Yes</td><td>Yes</td></tr>
<tr><td rowspan="2">Constraints of distribution networks</td><td>Demand-driven network issues</td><td colspan="2" rowspan="2">No</td><td>Yes</td><td>Yes</td><td>Yes</td><td>Yes</td><td>Yes</td></tr>
<tr><td>Generation-driven network issues</td><td>No</td><td>Yes</td><td colspan="2">No</td><td>Yes</td></tr>
<tr><td rowspan="2">Type of offers to solve network issues</td><td>Generation offers</td><td colspan="5">No</td><td>Yes</td><td>Yes</td></tr>
<tr><td>Demand offers</td><td colspan="6">No</td><td>Yes</td></tr>
<tr><td>Decision-making algorithm to select successful offers</td><td>Rule-based / optimization-based</td><td colspan="2">No</td><td>Rule-based</td><td colspan="3">Optimization-based (OPF)</td><td>OPF</td></tr>
</table>

- The modelling of a novel approach to determine the quantities and prices of aggregate flexibility services (net-demand adjustment) that could be unlocked from residential customers to support distribution networks.
- The provision of both generation offers (reducing demand) and demand offers (increasing demand) from aggregators to manage network constraints. This provides improvement from previous studies that are limited to generation offers.
- The realistic modelling of interactions between the DSO, aggregators and customers instead of using single centralized entity to directly control residential flexible assets.
- The modelling of an optimization-based approach to procure the best amounts of generation flexibility (reducing demand) and demand flexibility (increasing demand) from residential customers to manage thermal and voltage constraints.
- The incorporation of aggregators' offers in the decision-making algorithm provides a direct approach to define the incentives without the need to extensive iterations between the DSO and aggregators to agree on quantities and prices.

The rest of this paper is structured as follows: Section II provides an overview of the framework. Section III presents the formulations of OPF, the process to define offers and HEMS. The framework is demonstrated using an urban 11kV feeder with electric vehicles (EVs) and batteries in Section IV. The key remarks are given in Section V. Finally, the conclusions are drawn in Section VI.

II. FRAMEWORK OF THE TRANSACTIVE ENERGY SYSTEM FOR DISTRIBUTION NETWORK MANAGEMENT

The framework of the proposed TES is shown in Fig. 1. The figure describes graphically the process to solve congestions and voltage issues in distribution networks resulting from the response of residential customers to the energy market prices (£/MWh). The TES aims to procure flexibility services from residential customers to reschedule their controllable elements for the benefits of distribution networks. For this purpose, incentive-based price signals (£/MW) are produced during time intervals of network issues to remunerate residential customers who are contributing to managing network constraints. The framework also assumes the presence of spatially-distributed aggregators (e.g., an aggregator at each distribution substation) across distribution networks to interact with residential customers, the DSO and SO. The existence of aggregators is important particularly in countries with regulatory rules that do not allow DSOs to have direct access to the individual customers' meters. The proposed framework provides clear roles of residential customers, aggregators and DSOs. The details are explained as follows.

In response to the electricity energy market prices defined by the SO, each customer aims to minimize the daily energy payment through the optimal management of controllable flexible assets. For this purpose, the HEMS described in [7] and [31] is adopted to define the optimal daily schedule of EVs and batteries. The resulting customers' net-demand profiles are then aggregated and sent to the DSO through aggregators. The response of customers to the energy prices may result in the violations of network constraints. Thus, a distribution Network Management System (NMS) is introduced to check for the violations of network constraints. Based on the net-demand profiles submitted by aggregators, an AC power flow is run at each time step in the operational planning (e.g., one day) to calculate network voltages and power flows throughout lines and transformers. For any time step with congestion or voltages issues, the TES is triggered to procure flexibility services from aggregators to maintain network constraints within limits. The DSO requests offers from aggregators to modify their power schedules. In response to the DSO's request, each aggregator is connected to the TES platform to submit a set of offers to either reduce or increase the net-demand from the customers. Each offer

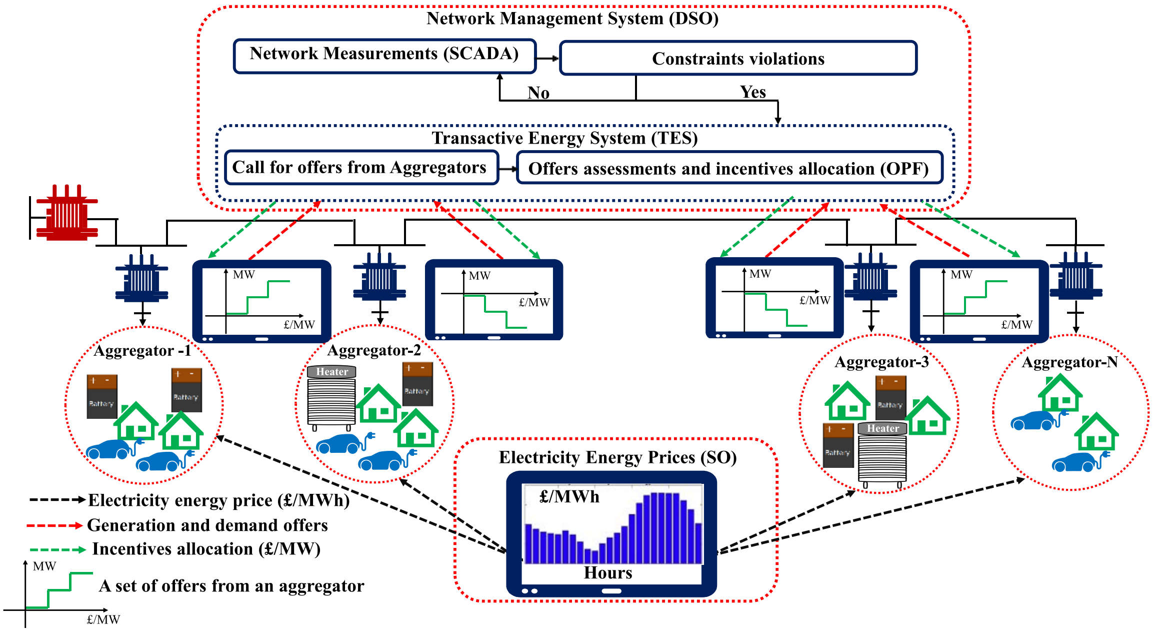


FIGURE 1. Framework of the transactive energy system in distribution networks.

provides the quantity of the potential net-demand adjustment (MW) and the corresponding price (£/MW). The quantities of the set of offers per aggregator are gradually increased from a small value of net-demand adjustment towards the maximum possible net- demand change. The prices of the set of offers also increase with the amounts of net-demand adjustments.

The type of offers requested from the aggregators (generation offers or demand offers) are defined according to the network operating conditions at the time step of triggering the TES. It is important to determine whether the causes of network issues are due to the significant increase in net-demand (demand-driven network issues) or excess export (generation-driven network issues). Also, the contributions of aggregators in the severity of network issues have to be defined to determine the type of requested offers. This is in particular necessary since the net-demand of aggregators could be either positive (demand) or negative (generation) due to the different response of residential customers to the energy prices. If it is found that the reduction of an aggregator's net-demand reduces the severity of network issues, generation offers will be requested accordingly. Demand offers will be requested from an aggregator if the increase of its net demand contributes positively to solving the network issues.

The quantities in the offers are determined according to the flexibility of individual residential customers to adjust their net-demand (e.g., shifting demand, discharging or charging batteries) in response to the predefined set of prices. Although the offer is placed at a particular time step, its delivery may have negative impacts in the subsequent time intervals and thus increase customers' electricity payments. For instance, the usage of batteries to solve demand-driven network issues in the early morning (e.g., voltage drop issues) may reduce the volume of stored energy and increase import during night periods that are mostly associated with high electricity market prices. Thus, the offers placed by the aggregators are defined to compensate the adverse impacts on customers' bills. At a particular offer's price, the HEMS is run per residential customer to determine the maximum net-demand change that each customer could deliver without affecting the desired daily electricity payment. To define adequately the flexibility per aggregator, the offers' prices are also gradually increased between their minimum and maximum values in small steps. The customers' response at each offer's price are aggregated to define the offer's quantity.

Once all the aggregators submit their offers to the DSO, an AC OPF-based optimization engine at the DSO's network management system identifies (selects) the successful generation and demand offers (single offer could be selected at most from an aggregator). Since the DSO will pay the cost of net-demand adjustments, the AC OPF is formulated to minimize the amounts of payments to the aggregators whilst respecting thermal and voltage constraints. The outcomes of the OPF are then notified to the aggregators to deliver the quantities of the successful offers. Then, the prices of successful offers are sent to individual customers (incentive-based price signal) to achieve the committed power.

III. MODELING OF THE TRANSACTIVE ENERGY SYSTEM

This section presents the modeling of the transactive energy system including the decision-making algorithm, the process to define aggregators' generation and demand offers as well as the HEMS.

A. DSO: DECISION-MAKING ALGORITHM

The decision-making algorithm at the DSO aims to identify the most feasible generation and demand offers from aggregators to solve the network issues resulting from the response of individual customers to the energy market prices. For this purpose, an AC OPF model is formulated to minimize the amounts of incentives given to the aggregators whilst respecting the thermal and voltage constraints. The necessity to trigger the OPF at a particular time step (set T indexed by t) is determined based on the existing network operating conditions. To check for congestions and voltage issues, AC power flows is run at each time step in the planning horizon.

To drive the OPF at a time step t^*, the active and reactive power of non-controllable loads (set D indexed by d) and the net-demand of aggregators (set A indexed by a) are all sent to the optimization engine. Further, the aggregators submit a set of offers upon the DSO's request to either increase net-demand (demand offers) or decrease net-demand (generation offers). Each generation offer (set I_G indexed by i_g) consists of both the amount of power generation $\Delta G_{a,i_g}^{offer}$ that could be injected (i.e., demand reductions) to the grid and the price π_{a,i_g}^{offer} to deliver it. In contrast, the quantities and prices of demand offers (set I_D indexed by i_d) represent the additional demand $\Delta D_{a,i_d}^{offer}$ (e.g., charging batteries) that could be created and the corresponding prices , π_{a,i_d}^{offer}. The quantities and prices of generation and demand offers are all modelled in the OPF as non-negative parameters. The generation and demand offers are determined according to the flexibility of residential customers to adjust their initial demand. It is worth to note that an aggregator could submit either generation or demand offers according to the DSO request as per the network operating conditions.

The objective function is formulated in (1) to minimize the cost of net-demand adjustment to solve network issues.

$$Min \sum\nolimits_{a\in A} \sum\nolimits_{i_g\in I_G} \Delta G_{a,i_g}^{offer} \pi_{a,i_g}^{offer} \beta_{a,i_g}^{offer} + \sum\nolimits_{a\in A} \sum\nolimits_{i_d\in I_D} \Delta D_{a,i_d}^{offer} \pi_{a,i_d}^{offer} \gamma_{a,i_d}^{offer} \quad (1)$$

where β_{a,i_g}^{offer} and γ_{a,i_d}^{offer} are binary variables used to define the status of generation and demand offers per each aggregator, respectively (e.g., $\beta_{a,i_g}^{offer} = 1$ means that the generation offer i_g from aggregator a is accepted). To guarantee the adoption of a single offer from each aggregator, the constraint in (2) is formulated. It is worth to highlight that it is possible that the DSO may not procure offers from an aggregator (e.g., offers with high prices). Therefore, the modelling considers the inclusion of an offer per aggregator whose quantities and prices are set to zero (i.e., no adjustment of net-demand).

$$\sum\nolimits_{i_d\in I_D} \gamma_{a,i_d}^{offer} + \sum\nolimits_{i_g\in I_G} \beta_{a,i_g}^{offer} = 1 : \quad \forall a \in A \quad (2)$$

By multiplying offers' quantities ($\Delta G_{a,i_g}^{offer}$, $\Delta D_{a,i_d}^{offer}$) and their adoption status (β_{a,i_g}^{offer}, γ_{a,i_d}^{offer}), the optimal levels of additional generation and demand (ΔG_a^*, ΔD_a^*) provided by each aggregator can be identified as given in (3) and (4); respectively. The aggregators are notified with the successful offers. Each aggregator is committed to adjust its initial net-demand at the time step $t^*(\tilde{p}_{a,t=t^*})$ according to the quantities of accepted generation and demand offers. Therefore, the committed active power of each aggregator ($p_{a,t=t^*}$) is formulated in (5).

$$\Delta G_a^* = \sum_{i_g\in I_G} \Delta G_{a,i_g}^{offer} \beta_{a,i_g}^{offer}; \quad \forall a \in A \quad (3)$$

$$\Delta D_a^* = \sum_{i_d\in I_D} \Delta D_{a,i_d}^{offer} \gamma_{a,i_d}^{offer}; \quad \forall a \in A \quad (4)$$

$$p_{a,t=t^*} = \tilde{p}_{a,t=t^*} + \Delta D_a^* - \Delta G_a^* \quad (5)$$

The applied incentives (π_a^{g*}, π_a^{d*}) in return of delivering the quantities in the accepted generation and demand offers are given in (6) and (7), respectively (i.e., prices defined by the aggregators in the accepted offers).

$$\pi_a^{g*} = \sum_{i_g\in I_G} \pi_{a,i_g}^{offer} \beta_{a,i_g}^{offer}; \quad \forall a \in A \quad (6)$$

$$\pi_a^{d*} = \sum_{i_d\in I_D} \pi_{a,i_d}^{offer} \gamma_{a,i_d}^{offer}; \quad \forall a \in A \quad (7)$$

The optimization problem is also subject to the traditional Kirchhoff's voltage and current laws (KVL and KCL) as well as to thermal and voltage constraints which are modelled to keep both power flows throughout the network branches (set L indexed by l) and network voltages all within limits.

At each bus (set B indexed by b), the balance of active and reactive power are given in the constraints (8) and (9), respectively.

$$p_x = \sum_{a\in A|\rho_a=b} p_{a,t=t^*} + \sum_{d\in D|\rho_d=b} p_d + \sum_{l\in L|\rho_{l=b}^{(1,2)}} f_l^{(1,2),(p)} \quad (8)$$

$$q_x = \sum_{a\in A|\rho_a=b} p_{a,t=t^*} tan\,(\phi_a) + \sum_{d\in D|\rho_d=b} q_d + \sum_{l\in L|\rho_{l=b}^{(1,2)}} f_l^{(1,2),(q)} \quad (9)$$

where ρ_u denotes the bus (b) to which each network element is connected ($u \subset \{a, d, l\}$). The modelling considers the active and reactive power of non-controllable loads (p_d, q_d) and the committed active power of aggregators ($p_{a,t=t^*}$) as well as power flows from the upstream grid (p_x, q_x). Further, the reactive power of aggregators is considered assuming a fixed power factor (ϕ_a). The KVL equations in [32] are used to calculate the active and the reactive power injections ($f_l^{(1,2),(P)}$, $f_l^{(1,2),(Q)}$) for each branch at the start and end bus (represented by 1 and 2, respectively). The voltage and thermal constraints (applied at the start and the end of each network branch l) are given in (10) and (11), respectively.

$$V_b^- \leq V_b \leq V_b^+; \quad \forall b \in B \quad (10)$$

$$\left(f_l^{(1,2),(p)}\right)^2 + \left(f_l^{(1,2),(q)}\right)^2 \leq \left(f_l^+\right)^2; \quad \forall l \in L \quad (11)$$

where V_b is the voltage magnitude at bus b, $V_b^{(-,+)}$ are the allowable voltage limits and $f_l^{(+)}$ is the thermal capacity of network branch l.

To solve the above Mixed Integer Non-Linear Programming problem (MINLP), the iterative approach in [33] is adopted. The binary decision variables related to the status of generation and demand offers (β_{a,i_g}^{offer}, γ_{a,i_d}^{offer}) are relaxed and considered as continuous variables whose values are between zero and one. This enables reducing the computational burden through the adoption of a Non-Linear Programming (NLP) optimization problem. However, these values need adjustment. To do so, a threshold, ε is defined to exclude offers with status values smaller than ε. The OPF is carried out iteratively until the status of offers are binary whilst increasing ε throughout the iterations (e.g., from 0.1 to 1.0 in steps of 0.1). This allows identifying the most feasible offers to solve technical issues (i.e., offers' status with unity values).

B. AGGREGATORS: GENERATION OFFERS

This Section provides the formulation to explain mathematically how the aggregators would respond to a call for generation offers at $t = t^*$ to reduce its initial net-demand at the time step t^* ($\tilde{p}_{a,t=t^*}$). The definition of aggregators' offers is quantified based on the flexibility of residential customers (set H indexed by h) to reduce demand in response to a generation offer's price π_{h,i_g}^{offer}. To do so, HEMS is run at each residential customer to adjust the control actions of flexible elements from t^* (i.e., time step when offers are requested) until the end of the day ($t \geq t^*$). Thus, the price signal sent to the HEMS consists of two components. The first component is the energy market prices (π_t^M) and the second component is the generation offer's price π_{h,i_g}^{offer} that is applied at t^* to remunerate demand reduction (£/MW). The resulting power profile $p_{h,i_g,t}$ from the HEMS is used to calculate the flexibility of the residential customer to provide generation offer. The quantity of the generation offer ($\Delta G_{h,i_g}^{offer}$) per residential customer is calculated in (12) as the difference between the initial residential power at $t = t^*$ ($\tilde{p}_{h,t=t^*}$) and the new adjusted power ($p_{h,i_g,t=t^*}$) that is obtained from the HEMS at a generation offer's price.

$$\Delta G_{h,i_g}^{offer} = \tilde{p}_{h,t=t^*} - p_{h,i_g,t=t^*} \tag{12}$$

Once generation offers from residential customers are quantified, the aggregators' offers can be defined $\Delta G_{a,i_g}^{offer}$, as given in (13).

$$\Delta G_{a,i_g}^{offer} = \sum_{h \in H | \rho_h = a} \Delta G_{h,i_g}^{offer} \tag{13}$$

where ρ_h indicates the aggregator of residential customer h. To enable the aggregator submitting a set of generation offers, the above process is repeated and the HEMS per residential customer is fed with different predefined values of generation offer prices π_{h,i_g}^{offer}. The adopted prices are gradually increased from zero in small steps to a large value that could trigger the maximum flexibility per residential customer to reduce demand. Mathematically, the objective of HEMS is formulated in (14) to maximize the amount of generation offer $\Delta G_{h,i_g}^{offer}$ (non-negative variable) that could be delivered at a generation offer's price π_{h,i_g}^{offer}.

$$Max\ \Delta G_{h,i_g}^{offer} \tag{14}$$

Since HEMS might be triggered multiple times in the day (in response to the DSO requests to solve network issues), it is important to preserve power consumption before the current time step (t^*), as formulated in (15).

$$p_{h,i_g,t} = \tilde{p}_{h,t}; \quad \forall t < t^* \tag{15}$$

The delivery of generation offers at $t = t^*$ may increase demand in the subsequent time steps ($t > t^*$) to satisfy customers' energy needs. However, this may increase electricity payments particularly when power consumption is moved to time intervals with higher energy prices. For this purpose, the constraint in (16) is formulated to ensure that revenues earned from delivering offers compensate the potential increase in electricity payments due to rescheduling. Thus, the overall daily electricity payment ($Cost_{h,i_g}^{daily}$) is maintained below a desired one ($Cost_h^{desired}$). For simplicity, it is assumed that the desired payment is the same as the one found by only responding to the energy market prices.

$$Cost_{h,i_g}^{daily} \leq Cost_h^{desired} \tag{16}$$

The daily electricity payment consists of three parts. The first part is related to the cost of electricity up to the current time step ($Cost_h^{t<t^*}$). Its value is calculated according to the previous power consumptions ($\tilde{p}_{h,t}$) and the energy market prices (π_t^M) as well as the revenues received from previous applied incentives, as given in (17).

$$Cost_h^{t<t^*} = \sum_{t=1}^{t^*-1} \left(\tilde{p}_{h,t}\pi_t^M \Delta t - \Delta G_{h,t}^* \pi_{h,t}^{g*} - \Delta D_{h,t}^* \pi_{h,t}^{d*}\right) \tag{17}$$

where Δt is the time step (in hour), $\Delta G_{h,t}^*$ and $\pi_{h,t}^{g*}$ are the quantities and prices of previously accepted generation offers, respectively. In contrast, $\Delta D_{h,t}^*$ and $\pi_{h,t}^{d*}$ are the quantities and the prices of previously accepted demand offers, respectively. The second and third part of electricity payment are the cost at the current time step ($Cost_{h,i_g}^{t=t^*}$) and the cost in the next time steps ($Cost_{h,i_g}^{t>t^*}$), as given in (18) and (19), respectively.

$$Cost_{h,i_g}^{t=t^*} = p_{h,i_g,t=t^*}\pi_{t=t^*}^M \Delta t - \Delta G_{h,i_g}^{offer} \pi_{h,i_g}^{offer} \tag{18}$$

$$Cost_{h,i\ g}^{t>t^*} = \sum_{t=t^*+1}^{T} p_{h,i_g,t}\pi_t^M \Delta t \tag{19}$$

Based on above, the electricity payment is given in (20).

$$Cost_{h,i_g}^{daily} = Cost_h^{t<t^*} + Cost_{h,i_g}^{t=t^*} + Cost_{h,i_g}^{t>t^*} \tag{20}$$

C. AGGREGATORS: DEMAND OFFERS

Here, the objective of HEMS is formulated in (21) to maximize the amount of demand offer ($\Delta D^{offer}_{h,i_d}$) in response to a particular incentive $\pi^{offer}_{i_d}$. The demand offer per each residential customer is mathematically formulated in (22) as the difference between the value of demand at $t = t^*$ in the new adjusted power profile ($p_{h,i_d,t=t^*}$) and the initial residential power profile ($\tilde{p}_{h,t=t^*}$). Like generation offers, demand offers are restricted to maintain customers' desired daily electricity payment. Thus, the objective of HEMS is subject to the constraints in (15)–(17) and (19)–(20). The cost at the current time step ($Cost^{t=t^*}_{h,i_d}$) is given in (23).

$$Max\, \Delta D^{offer}_{h,i_d} \tag{21}$$

$$\Delta D^{offer}_{h,i_d} = p_{h,i_d,t=t^*} - \tilde{p}_{h,t=t^*} \tag{22}$$

$$Cost^{t=t^*}_{h,i_d} = p_{h,i_d,t=t^*}\pi^M_{t=t^*}\Delta t - \Delta D^{offer}_{h,i_d}\pi^{offer}_{i_d} \tag{23}$$

Once demand offers are quantified per each customer, the aggregators' offers can be then found, as given in (24).

$$\Delta D^{offer}_{a,i_d} = \sum_{h\in H|\rho_{h=a}} \Delta D^{offer}_{h,i_d} \tag{24}$$

The HEMS at each residential customer is also run for different values of offers' prices to determine the quantities of demand offers per aggregator.

D. HEMS: CONTROLLABLE ELEMENTS

The flexibility of residential customers to respond to market prices and the provision of generation and demand offers can be achieved by controlling the output power of residential batteries (set ST indexed by st), $p_{st,h,t}$, and the power consumption of EVs (set EV indexed by ev), $p_{ev,h,t}$. Further to the objectives in (14) and (21), the HEMS is also called (at $t = 1$) to determine the minimum electricity payment that could be achieved whilst responding only to market prices ($Cost^{desired}_h$), as modelled in (25).

$$Cost^{desired}_h = Min \sum_{t=1}^{T} p^M_{h,t}\pi^M_t \Delta t \tag{25}$$

where $p^M_{h,t}$ is power consumption responding to energy prices.

The objectives of HEMS to provide generation and demand offers in (14) and (21), respectively as well as the objective in (25) are all subject to set of operational constraints. For this purpose, the formulation proposed in [7] and [31] to model batteries and EVs are adopted. For completeness, the formulations are given. They are presented independently of generation offers (set I_G indexed by i_g) and demand offers (set I_D indexed by i_d) for the sake of simplicity.

The active power output of residential batteries is modelled using two non-negative variables ($p^{ch}_{st,h,t}, p^{dis}_{st,h,t}$) to indicate charging and discharging power, respectively. The values of both variables are maintained within the battery rating $P^{rated}_{st,h}$. The battery output power $p_{st,h,t}$ could be either positive (discharge) or negative (charge). Also, a binary variable $\alpha_{st,h,t}$ is adopted to model the status of the battery at each time step. Further, the stored energy in battery $E^{store}_{st,h,t}$ at each time step is restricted below its energy rating $E^{rated}_{st,h}$. The corresponding constraints are given in (26) –(32).

$$0 \le p^{dis}_{st,h,t} \le P^{rated}_{st,h} \tag{26}$$

$$0 \le p^{ch}_{st,h,t} \le P^{rated}_{st,h} \tag{27}$$

$$p_{st,h,t} = p^{dis}_{st,h,t} - p^{ch}_{st,h,t} \tag{28}$$

$$0 \le p^{dis}_{st,h,t} \le \alpha_{st,h,t} \times P^{rated}_{st,h} \tag{29}$$

$$0 \le p^{ch}_{st,h,t} \le \left(1 - \alpha_{st,h,t}\right) \times P^{rated}_{st,h} \tag{30}$$

$$E^{store}_{st,h,t} = E^{store}_{st,h,t-1} + \left(p^{ch}_{st,h,t}\eta^{ch} - \frac{p^{dis}_{st,h,t}}{\eta^{dis}}\right) \times \Delta t \tag{31}$$

$$E^{store}_{st,h,t} \le E^{rated}_{st,h} \tag{32}$$

where η^{ch} and η^{dis} are the charging and discharging efficiencies, respectively.

The HEMS also manages the charging actions of EV to achieve the required energy level $E_{ev,h}$ between the arrival and the departure time step $T_{ev,h} \equiv \left[T^{arr}_{ev,h}, T^{dep}_{ev,h}\right]$. This is done by controlling the charging power $p_{ev,h,t}$ within its rated value $P^{rated}_{ev,h}$. The EV constraints are given in (33) –(35).

$$p_{ev,h,t} \le P^{rated}_{ev,h}; \quad \forall t \in T_{ev,h} \tag{33}$$

$$p_{ev,h,t} = 0; \quad \forall t \notin T_{ev,h} \tag{34}$$

$$\sum_{t\in T_{ev,h}} \left(p_{ev,h,t} \times \Delta t\right) = E_{ev,h} \tag{35}$$

The resulting demand of a house $p^M_{h,t}$ is formulated using the power balance constraint in (36) considering critical demand of uncontrollable residential assets ($p^{CD}_{h,t}$).

$$p^M_{h,t} = p^{CD}_{h,t} + p_{ev,h,t} - p_{st,h,t} \tag{36}$$

IV. RESULTS

A. CASE STUDY: DESCRIPTIONS

The proposed TES framework is applied to a UK urban 11kV feeder with 2700 residential customers. The single-line representation of the network is given in Fig. 2 [34]. The residential load profiles are produced using the tool developed by the Centre for Renewable Energy Systems Technology (CREST) considering half-hourly resolution [35]. It is considered that each customer has a 14kWh battery with round trip efficiency of 90% and power rating of 3.6kW [36]. Further, it is assumed that 50% of the residential customers have EVs. The charging profiles of EVs are produced according to the statistics provided in [7]. This includes the users' driven distances, arrival times and departure times. For demonstration purposes, a price signal from the UK electricity market is adopted from [37] and provided in Fig. 3. It is also assumed the existence of a single aggregator per distribution transformer to facilitate the interactions between the downstream residential customers and the TES. The modeling language AIMMS [38] is used to formulate the HEMS and the decision-making algorithm at the TES. The HEMS is formulated as a Mixed

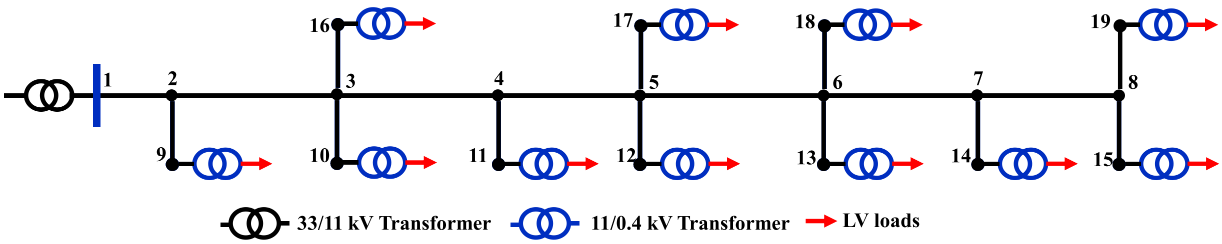


FIGURE 2. UKGDS 11 kV feeder.

Integer Linear Programming (MILP) optimization problem and it is solved using the CPLEX solver [39]. In contrast, the CONOPT solver [40] is utilized to determine the decision-variables of the TES decision-making algorithm whose formulation is a Non-Linear Programming (NLP) optimization problem.

B. IMPACT ASSESSMENTS OF DYNAMIC RESIDENTIAL PRICING

To demonstrate the benefits of the proposed TES, this section presents the response of residential customers to the adopted price signal and the corresponding technical impacts on the 11kV feeder. For this purpose, the HEMS presented in Section III-D is employed at residential customers to minimize electricity payments. For each customer with EV, the HEMS defines both the best time to start charging and the charging power profiles. Also, the HEMS determines the optimal charging and discharging actions of batteries.

For demonstration purposes, Fig. 4 shows both the resulting aggregate charging profiles of EVs (in red) and the power outputs of batteries (in blue) of all the residential customers. To reduce electricity payments, it can be seen that most of the power consumption of EVs is scheduled towards the lowest-price time intervals (i.e., between 2:30 –7:00 a.m.). Taking into account that the charging actions of EVs must occur between their arrival and departure times, the flexibility to schedule EVs is limited. Thus, this figure shows that part of the EVs power consumption is scheduled between 00:00 and 2:00 a.m. whose energy prices are 18% higher than the lowest price. It is worth to highlight that diversity in EVs' charging preferences could be seen positively from the perspective of distribution networks. The diversity supports reducing the peak demand in the network.

However, the wide-scale adoption of batteries (as considered here) affects the diversity of demand. Batteries improve the ability of HEMS to manage the net-demand of residential customers to reduce electricity payments. Different from EVs, batteries are more flexible to be controlled to maximize the financial benefits of customers. Batteries could be charged during the lowest-price intervals. The resulting stored energy can be then utilized to support customers' energy consumption needs at the highest price intervals (05:00 –06:00 p.m.). During the highest price intervals, it is also possible to harness the stored energy to create additional revenues for residential customers by injecting power back to the grid. This can be clearly seen in the aggregate profiles of batteries presented in Fig. 4.

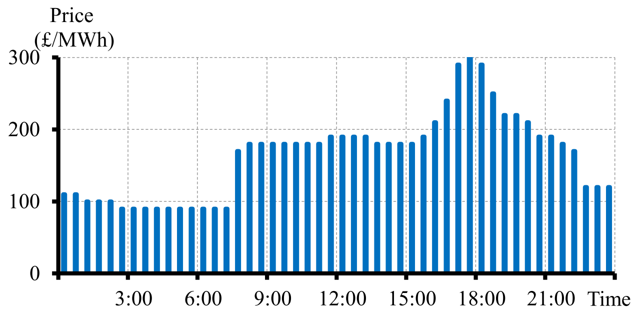


FIGURE 3. Half-hourly daily market price signal (£/MWh).

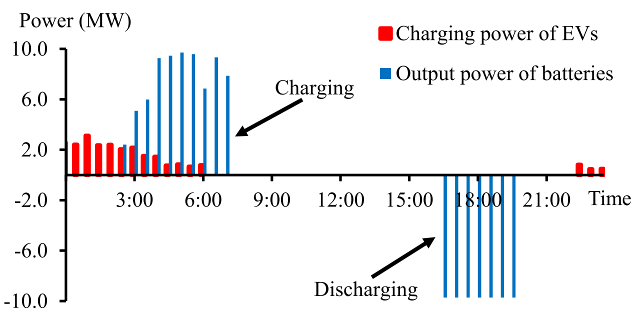


FIGURE 4. Aggregate daily power profiles (MW) for EVs and batteries under dynamic residential pricing.

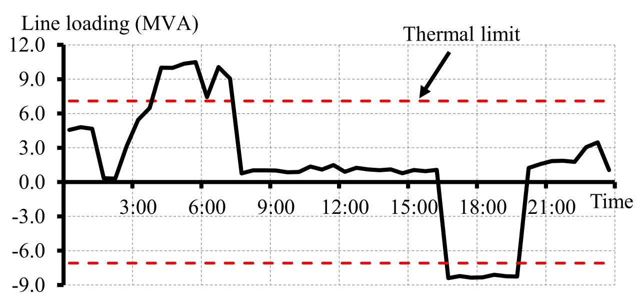


FIGURE 5. Power flow at head of the feeder (MVA) under dynamic residential pricing (before the functioning of TES).

The charging actions all are occurred between 2:30 –7:00 a.m. In contrast, the discharging actions are placed between 4:30 –.7:30 p.m. Once the response of residential customers are found, power flow simulation is carried out to assess the impacts on the 11kV feeder. The power flows throughout lines and network voltages are found at each time step (half- hourly). For illustration purposes, the power flows at the head of the feeder are presented in Fig. 5 along with the thermal limit of the feeder (i.e., continuous ratings of conductors whose values are obtained in practice from the manufacturers' datasheets). It can be seen that the response of customers to the price signal increases the feeder's loading above its thermal limit. In particular, its loading reaches 10.5MW (i.e., 50% overloading) between 4:00 a.m. and 7:00 a.m. due to the charging actions of EVs and batteries. Further, the significant export from customers at time intervals with high energy prices creates reverse power flows and congestion issues (4:30 –.7:30 p.m.).

Based on the above, the results clearly demonstrate the impacts of dynamic residential pricing on the technical constraints of distribution networks particularly at both the lowest-price and highest-price time intervals. This in turn highlights the need to request both generation offers (reducing demand) and demand offers (increasing demand) from residential customers to solve demand-driven and generation-driven network issues, respectively.

C. TES FOR CONGESTION MANAGEMENT: GENERATION OFFERS

This section demonstrates the process to solve congestions between 4:00-7:00 a.m. due to excess import. To cater for network issues, the aggregators are requested to submit generation offers (i.e., offers to reduce demand). Each offer determines the quantity of demand reduction from the last schedule and the corresponding price. The ability of an aggregator to reduce demand is quantified in response to a set of predefined amounts of incentives whose values are starting from 0£/MW (no incentive) to 150£/MW in small steps of 5£/MW. The selected incentive is applied at the time of network issues. Thus, the price signal consists of both the original energy market price (£/MWh) and the value of incentive (£/MW) that rewards power change from the last schedule. In response to the updated price signal, the HEMS at each individual customer aims to determine the maximum generation offer (i.e., demand reduction) whilst achieving the same total daily energy cost. Fig. 6 shows the response of an aggregator with 300 customers to an incentive of 100£/MW applied at 4:00 a.m. For this aggregator, each customer has EV and battery. With the adopted incentive (blue line), it can be seen in Fig. 6 (a) that the aggregator exports 0.9MW back to the grid at 4:00 a.m. Compared to the previous aggregator's power at no-incentive (imported power of 1.2MW), the amount of generation offer is 2.1MW. It can be noticed in Fig. 6 (b) that the resulting generation offer is mostly obtained from batteries. Their charging status at 4:00 a.m. are modified from charging to discharging. In particular, the discharged

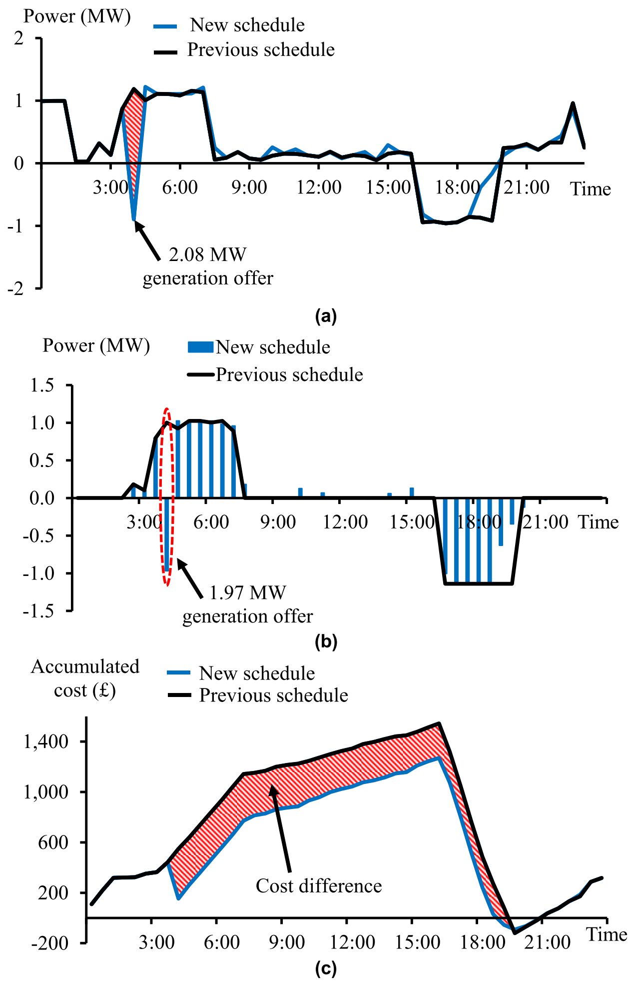


FIGURE 6. Generation offers at 04:00 a.m. from an aggregator with 300 customers (each customer with EV and battery) at incentive of 100£/MW: (a) power profile of the aggregator (MW), (b) power profile of batteries (MW) and (c) accumulated energy payments (£).

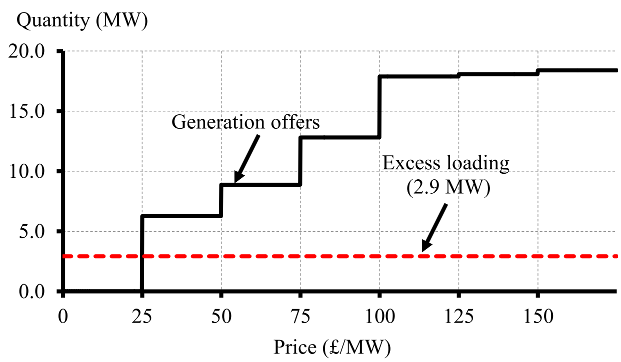


FIGURE 7. Total generation offers from aggregators at 4:00 a.m.

power becomes 0.97MW. It is important to highlight that the delivery of generation offer is at the expense of stored energy in batteries that is originally being used to support local energy consumption in the next time steps. Thus, the aggregator's power increases slightly during time intervals

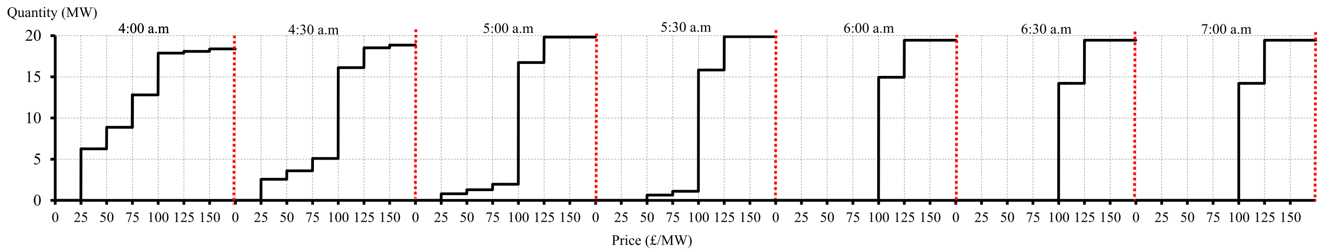


FIGURE 8. Generation offers from aggregators between 04:00 a.m. and 07:00 a.m.

TABLE 2. Accepted generation offers and incentives Between 04:00 a.m. and 07:00 a.m.

	4:00	4:30	5:00	5:30	6:00	6:30	7:00
Excess Loading (MW)	2.9	2.6	3.6	3.8	3.3	3.4	3.9
Total accepted generation offers (MW)	3.7	2.6	5.0	4.4	5.1	4.3	5.0
Average incentive (£/MW)	25	25	87	93	100	100	100
Total incentive payments (£)	92	64	436	409	505	432	504

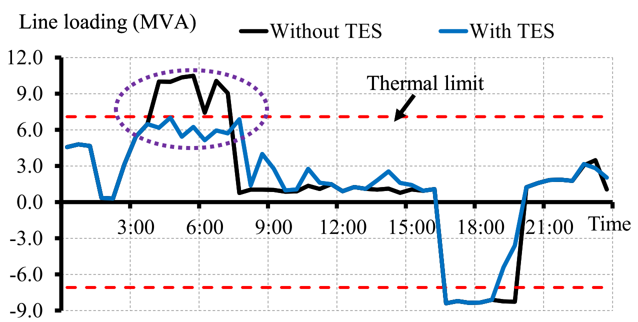


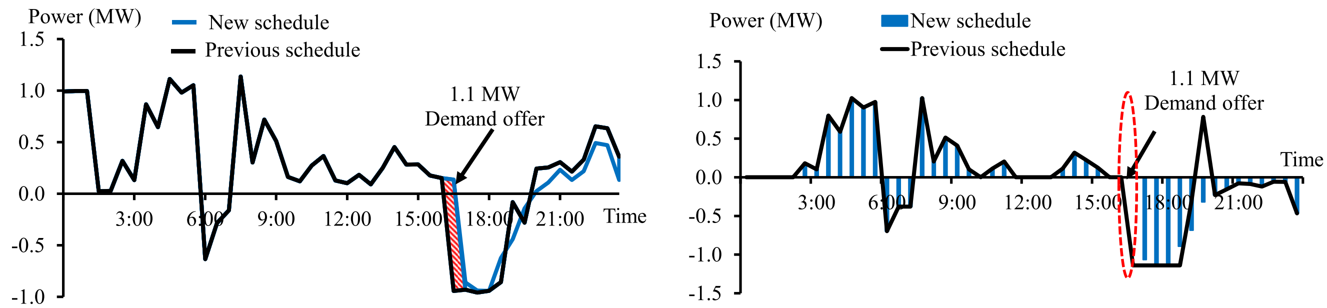
FIGURE 9. Power flow at head of the feeder (MVA) with procuring generation offers between 4:00 a.m. and 7:00 a.m.

between 7:30 a.m. and 4:00 p.m. Further, the volume of discharged energy between 4:30 p.m. and 7:30 p.m. becomes smaller (i.e., smaller revenues). However, the amount of incentives received at 4:00 a.m. (208£) compensates and balances the financial adverse impacts. This can be clearly seen in Fig. 6 (c). The total daily energy payments of all the customers at the end of the day (318 £) is the same as the one achieved by only responding to the energy market prices (black line). Thus, the net-demand change of 1.97 MW represents the maximum residential flexibility that could be triggered in response to an incentive of 100 £/MW whilst respecting the customers' desired daily energy payments. It is also worth to note that it might be possible to unlock larger volume of residential flexibility by increasing the applied incentive. However, this depends on the constraints of controllable appliances.

The DSO collects generation offers from the aggregators. The submitted offers depend on the number of residential customers and the type of controllable elements within each aggregator. For illustration, the resulting offers are aggregated and presented in Fig. 7. The figure shows the amount of generation offer in response to each incentive. It can be noticed that the minimum incentive to trigger generation offers is 25£/MW. Below this incentive, the financial returns are not enough to compensate the adverse impacts on the customers' energy bills. Also, the amount of generation offers increases with the adoption of higher incentives. The maximum generation offer that could be achieved is 18 MW. However, the marginal increase in generation offers becomes smaller after an incentive of 125£/MW. This staircase curve demonstrates the importance of defining the proper value of incentive to trigger the required amount of generation offers from aggregators. For instance, it is not possible to increase the total amount of generation offers when the applied incentive is above 25£/MW and smaller than 50£/MW.

To determine the accepted offers and incentives, the DSO runs the proposed TES algorithm. At 4:00 a.m., it is possible to decide the proper amount of incentive graphically. It can be seen that the cross between the excess loading of 2.9MW and the generation offers' curve is going to be the incentive required to solve congestions. Therefore, an incentive value of 25£/MW is the minimum one to maintain power flows at the head of the feeder below its limit. By using the OPF, it is found that the total amount of accepted offers is 3.7MW which makes about 59% of the available generation offers (6.3MW). This shows the effectiveness of the OPF to identify the successful offers to manage network constraints whilst minimizing the incentives paid by the DSO to the aggregators.

The above process is repeated at each time step with overloads due to excess demand (4:30 a.m.–7:00 a.m.). Fig. 8 presents a summary of the total generation offers. The accepted offers and the resulting incentives are given in Table 2. It can be noticed that the maximum amount of generation offers (19.4MW) is almost the same throughout the time steps (see Fig. 8). However, the incentive to release this maximum gradually increases from a time step to the next one. For instance, an incentive of 25£/MW is able to trigger generation offer at 4:00 a.m. compared to 100£/MW



(a) (b)

FIGURE 10. **Demand offers at 04:30 p.m. from an aggregator with 300 customers (each customer with EV and battery) at incentive of 100£/MW: (a) Power profile of the aggregator (MW), (b) power profile of batteries (MW).**

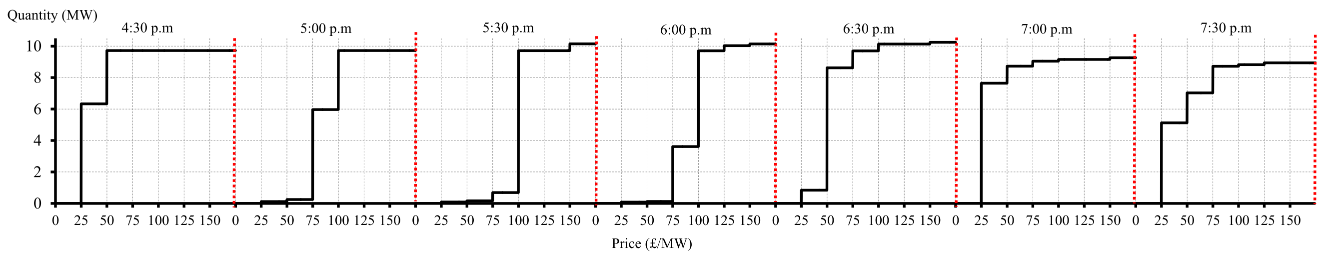


FIGURE 11. **Demand offers from aggregators between 04:30 p.m. and 07:30 p.m.**

TABLE 3. **Accepted demand offers and incentives between 04:30 p.m. and 07:30 p.m.**

	4:30	5:00	5:30	6:00	6:30	7:00	7:30
Excess Loading (MW)	1.3	1.1	1.3	1.2	1.0	0.20	0.02
Total accepted demand offers (MW)	1.96	1.3	1.8	1.8	1.4	1.08	1.08
Average incentive (£/MW)	25	71	90	73	35	25	25
Total incentive payments (£)	49	97	160	133	48	27	27

at 6:00 a.m. This increases the value of procured power (£/MW) from aggregators. For example, the optimal incentive at 6:00 a.m. is 38% (1.4MW) higher than the one at 4:00 a.m. (see Table 2). Since the accepted offers are selected from discrete values of aggregators' offers, it is also worth to note that the quantities of accepted offers are slightly higher than what it is exactly required to alleviate congestions. To this end, the application of TES between 4:00 a.m. and 7:00 a.m. enables managing effectively network constraints through procuring the adequate amount of generation offers from aggregators. During those time intervals, the power flows are maintained within limits as shown in Fig. 9. However, generation-driven network issues between 4:30 p.m.–6:30 p.m. (due to excess export from residential customers) have not been yet solved.

D. TES FOR CONGESTION MANAGEMENT: DEMAND OFFERS

Here, TES is utilized to solve congestions due to excess export between 4:30 p.m.–6:30 p.m. (i.e., reverse power flows as shown in Fig. 9). To do so, aggregators are requested to submit demand offers (i.e., reduce export) to decrease intensities of reverse power flows and alleviate congestions. Like generation offers, the amounts of demand offers are quantified in response to a set of incentives (from 0£/MW to 150£/MW in steps of 5£/MW).

For illustration purposes, Fig, 10 (a) presents the profile of an aggregator with 300 customers with only responding to the energy market prices. This aggregator maximizes energy exports back to the grid to maximize its revenues from the sold energy to the system operator at high prices of 240£/MWh. The maximum export reaches 0.94MW. With an incentive of 100£/MW applied at 4:30 p.m. (blue line), the aggregator is encouraged to reduce export to deliver demand offer. This is done by rescheduling the control actions of batteries from the last schedule (black line). It can be seen in Fig. 10 (b) that batteries go into idling mode at 4:30 p.m. with zero output power (i.e., discharging is stopped). This enables the provision of demand offer of 1.1MW. To compensate revenues' losses, the volume of discharged power is increased in the subsequent time steps. To cope with any network issues resulting from rescheduling, the TES algorithm continues monitoring network' operating conditions and defines the proper amount of incentives. The results are summarized in Fig. 11 and Table 3. Different from generation offers, there are variations in the energy market prices when demand offers are requested. This in turn affects the response of aggregators

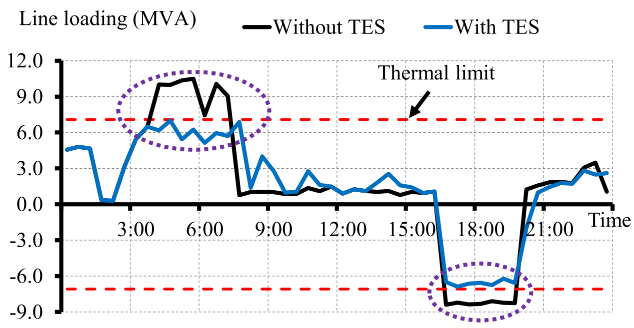


FIGURE 12. Power flow at head of the feeder (MVA) with procuring generation offers (4:00 a.m.-7:00 a.m.) and demand offers (4:30 p.m. -7:30 p.m.).

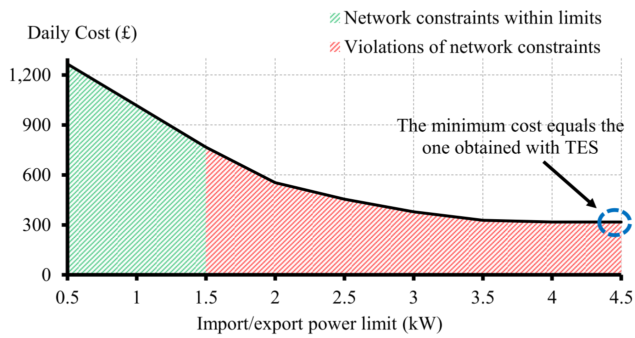


FIGURE 13. Management of network constraints using predefined import and export power limits: Daily energy cost versus different residential power limits for an aggregator with 300 customers (each customer with EV and battery).

to the adopted incentives. In particular, the allocated incentives to reduce export (i.e., demand offers) depend on the variations in energy market prices and the intensity of excess loading as well as the constraints of residential controllable appliances.

During time intervals with relatively high energy prices (i.e., 5:00 p.m. – 6:00 p.m.), the aggregators require higher amounts of incentives to reduce export. For instance, the minimum incentive to trigger demand offers at 5:00 p.m. is 75£/MW which is 300% higher than what is needed at 04:30 p.m. (25£/MW). To release the maximum flexibility to deliver demand offers, higher amounts of incentives are also needed. The incentive required to achieve a demand offer of 10MW at 5:00 p.m. is double the one used at 04:30 p.m. when the energy market price is relatively small. The variations in energy prices also affect the total amount of incentives paid to aggregators. To cope with excess loading of 1.3MW at 5:30 p.m., the total amount of incentives is 327% higher than the one at 04:30 p.m. (49£). It can be also seen that the amounts of accepted offers depend on the volume of excess loading. In particular, 1.4% of the available offers is only accepted at 7:30 p.m. with excess loading of 2%. The continuous procurement of generation and demand offers enables managing effectively network constraints throughout the day. For comparison purposes, the final line's loading with TES is given in Fig. 12 along with the original loading.

E. PERFORMANCE COMPARISON OF TES

For completeness, this Section aims to compare the performance of the proposed TES-based framework against other approaches proposed in the literature. For this purpose, the rule-based approach proposed in the studies [21], [22], [23], [24], [25] to mitigate the impacts on distribution networks is adopted. The approach considers managing the response of residential demand to the market prices below predefined export and import power limits. The approach is applied to the UK urban 11kV feeder in Fig. 2 with 2700 residential customers. The effects of different values of power limits on both the management of network constraints and the reduction in daily energy cost of aggregators are also quantified.

For demonstration purposes, Fig.13 shows the daily energy cost of an aggregator with 300 customers (each customer with EV and battery) for different power limits starting from 0.5 kW to 4.5 kW per residential customer (in steps of 0.5 kW). From the aggregators' perspectives, the adoption of a large value of power limit allows customers to almost freely exchange power from/to the distribution network to minimize their energy bills. The figure shows a significant reduction in the daily energy cost with large values of power limits. In particular, the energy cost at a power limit of 4.5 kW is 75% smaller than the one obtained at a conservative limit of 0.5 kW. However, the adoption of a large power limit results in network issues (shaded area in red). The results show that the selection of a power limit larger than 1.5 kW is not feasible from the perspective of distribution networks. Thus, deciding the most-adequate value of power limit to manage network constraints effectively (i.e., below 1.5 kW per residential customer) is at the expense of minimizing energy cost. In contrast, the TES-based framework provides better performance for both the customers and the distribution networks. The TES-framework allows customers to minimize their bills whilst managing network constraints effectively. In particular, it is found that the energy cost with TES equals the minimum possible energy cost that could be achieved by using large power limit (4.5 kW per residential customer). Also, the power flows of lines and transformers as well as network voltages by using TES are all managed effectively (see Fig. 12).

V. KEY REMARKS

For the benefits of the readers, the key remarks resulting from the application of the proposed TES framework are summarized as follows:

- The control of residential batteries for the benefits of customers (reducing electricity bills) creates new peak demand of distribution networks during the lowest price intervals. Further, the discharge of batteries during the highest price time intervals to maximize revenues from sold energy causes congestions in distribution networks.

- The superposition of energy dynamic market prices with adequate incentive supports customers to reschedule the operation of their controllable elements for the benefits of distribution networks to solve network issues.
- The generation and demand offers from aggregators to solve network issues are found effective to represent the flexibility of individual residential customers to manage their net-demand in response to predefined set of incentives.
- The staircase curve between the quantities and the prices of offers demonstrates the importance of defining the proper value of incentive to trigger the required amount of residential flexibility.
- The adoption of higher incentives allows increasing the quantities of offers (net-demand change). However, the marginal increase in offers becomes smaller after a particular incentive value which represents the maximum amount of flexibility that could be triggered from an aggregator.
- The application of TES enables managing network constraints through procuring the adequate amount of generation/demand offers from aggregators. In particular, the power flows at the head of the feeder with TES are maintained within limits. However, the incentive required to release a particular amount of residential flexibility to solve network issues increases from a time step to the next one.

VI. CONCLUSION

This work presents a framework to manage congestions and voltage issues in distribution networks resulting from the wide-scale adoption of dynamic residential pricing whose price signals are defined from the perspective of the bulk power system. The management of network constraints are carried based on the concept of Transactive Energy System (TES). To solve network issues, offers are requested from aggregators that are spatially distributed across distribution networks to either reduce demand (generation offers) or increase demand (demand offers). The offers are placed according to residential customers' flexibility to modify their last schedules in return of adequate amounts of incentives. For this purpose, the optimal control actions of residential flexible assets particularly electrical vehicles (EVs) and batteries are determined using the Home Energy Management System (HEMS), which is formulated as a Mixed Integer Linear Programming (MILP) optimization problem. Further, an AC Optimal Power Flow (OPF) algorithm is modelled to optimally identify the best aggregators' offers to respect network constraints with the minimum amounts of incentives. The effectiveness of the TES-based framework is demonstrated on an 11kV urban distribution feeder with 2700 residential customers with EVs and batteries.

The results demonstrate the conflicting interactions between distribution networks and residential time-differentiated pricing for the benefits of the bulk power system. By controlling residential demand to minimize electricity payments, the natural diversity of customers' net-demand is affected. In particular, the results show that most of customers' power consumption is moved towards the lowest-price time intervals whilst increasing energy export at the highest-price to maximize revenues from selling energy. For the studied feeder, the resulting significant import and reverse power flows cause congestions.

Further, it is found that the TES-based framework enables managing effectively network constraints by procuring generation and demand offers. From customers' perspective, the allocated incentives maintain desired electricity payments and compensate adverse financial impacts due to rescheduling. The results also demonstrate that the allocated incentives are influenced by energy prices. In particular, larger amounts of incentives are required at the highest-price to trigger flexibility to deliver demand offers. The results also demonstrate that customers' flexibility is progressively reduced throughout the day. This in turn leads to higher amounts of incentives.

It is important to highlight that the implementation of the TES-framework in practice requires addressing information-related challenges such as communication issues (e.g., synchronization), measurement errors and privacy of customers as well as customers' commitment to the accepted offers.

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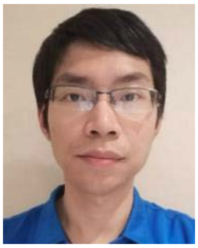

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