A nested transactive energy market model to trade demand-side flexibility of residential consumers

Mohammad Sohrab Hasan Nizami, *Student Member, IEEE,* M. J. Hossain, *Senior Member, IEEE,* and Khizir Mahmud, *Student Member, IEEE*

***Abstract*—A nested transactive energy (TE) market methodology is presented in this paper for the effective utilization of demand-side flexibility of small-scale residential consumers. The consumers' flexibilities are traded in a local flexibility market to prevent transformer overloading, whereas the demand-side flexibilities are traded in an event-triggered central wholesale demand response market after successive aggregation in the intermediate layers. A two-stage optimization-based scheduling model is presented to optimize the transactive bidding of residential consumers with on-site distributed energy resources and controllable loads. The optimal market methodologies are presented for the integrated TE markets to ensure economic trading for all involved stakeholders. The proposed methodology is numerically validated by simulation studies for different consumer participation levels, and the case studies indicate the efficacy of the proposed methodology for economically feasible procurement of consumer flexibility for transformer overloading and wholesale peak-price events. Results also illustrate that the proposed method offers 2.8-14 times more profits to the participating consumers than the energy-supply incentives according to existing retail tariff structures even considering their thermal discomfort and cycle-aging of storage units for the flexibility support.**

***Index Terms*—Transactive Energy, Demand Side Management, Demand Response, Local Flexibility Market, Nested Market**

NOMENCLATURE

Indices and Sets

$t \in \mathcal{T}$	Time periods $\in \{1, 2, ..., T\}$
$i \in \mathcal{I}$	Flexible consumers $\in \{1, 2, ..., I\}$
$j \in \mathcal{J}$	Non-flexible consumers $\in \{1, 2, ..., J\}$
$b \in \mathcal{B}$	Storage units $\in \{1, 2, ..., B\}$
$s \in \mathcal{S}$	External building surfaces $\in \{1, 2, ..., S\}$
$m \in \mathcal{M}$	Steps in bid function $\in \{1, 2, ..., M\}$
$n \in \mathcal{N}$	Local areas/aggregators $\in \{1, 2, ..., N\}$
$k \in \mathcal{K}$	DR aggregators $\in \{1, 2, ..., K\}$

Parameters

λ^{+}/λ^{-}	Energy demand and supply tariff [$/kWh]
Δt	Duration of time period [hour]
C^{R}	Storage unit replacement cost [$ AUD]
ω	Coefficient for thermal discomfort [$/° C]
θ^{set}	Thermostat set-point temperature
κ	Coefficient-of-performance (CoP) of the AC
Q^{g}	Internal heat gain of the building [kW]
β_s	Heat transfer coefficient [W/m^{2}K]
A_s	Building surface area [m^2]
θ^{o}	Ambient temperature [°C]
ρ, V, C^{th}	Density [kg/m^3], volume [m^3], and specific heat capacity [J/kg°C] of the building
$\overline{\theta}, \underline{\theta}$	Indoor temperature limits [°C]
P^{cn}, P^{dn}	Nominal charging/discharging power [kW]
η^{c}, η^{d}	Charging and discharging efficiencies
E^{cap}	Maximum storage capacity [kWh]
$\overline{\sigma_b}, \underline{\sigma_b}$	Maximum and minimum SoC of storage b
P^{il}	Power demand of inelastic building load [kW]
P^{g}	Power generation of residential DG unit [kW]

Variables

P^{+}/P^{-}	Power demand/supply from/to the grid [kW]
C, Φ, Ω	Electricity cost, Storage degradation cost and Thermal discomfort cost [$ AUD]
P^{ac}	Power consumption of AC [kW]
P^{c}/P^{d}	Storage charging/discharging power [kW]
θ	Indoor temperature [°C]
x, y, z	Binary optimization variables $\in \{0, 1\}$
σ, γ	State of charge and depth of discharge

Mohammad Sohrab Hasan Nizami is with the School of Engineering, Macquarie University, Sydney, NSW 2109, Australia (Email: sohrab.nizami@students.mq.edu.au).

M. J. Hossain is with the School of Electrical and Data Engineering, University of Technology Sydney, NSW-2007, Australia (Email: jahangir.hossain@uts.edu.au).

Khizir Mahmud is with the School of Electrical Engineering and Telecommunications, University of New South Wales, NSW 2052, Australia (Email: khizir.mahmud@unsw.edu.au).

I. INTRODUCTION

THE decentralization and decarbonization of the power grid have steered a rapid proliferation of renewable-based small-scale distributed energy resources (DER). Consequently, most consumers of low-voltage (LV) residential networks are now equipped with various on-site distributed generation (DG) units with or without storage facilities. Besides, residential energy demand is increasing due to the increased integration of electric vehicles (EV) and heat pumps (HP). The indeterminacy of renewable-based DER units, myopic consumer behavior for appliance usages, and growing energy demand impose various capacity challenges to the local grid operators (LGO) of residential LV networks including transformer overloading and local voltage-constraint violations [1]. Moreover, the fluctuating energy profiles of such consumers require fast and dynamic energy-balance measures to maintain reliable energy supply [2].

The digitalization of the grid allows the utilization of the demand-side flexibilities using demand response (DR) and demand-side management (DSM) strategies to address local grid-capacity issues and enhance energy-balance when grid reliability is jeopardized [2]–[4]. While traditional DR and DSM limit consumers' profitability and raise privacy concerns [3], [4], an advanced variant, known as the transactive energy (TE) framework, enhances the utilization of demand-side flexibilities for improved grid reliability and energy-balance efficiency [5]. The TE framework uses economic and market-based constructs for local energy balance while considering the reliability constraints of the grid [6]. The TE-based demonstration projects in [7]–[9] show that it allows the LGO to effectively use local resources (energy supply from DG units [7], [8] and consumers' demand-reduction flexibility [9]) to maintain reliable energy supply during peak-demand periods. It also allows responsive consumers to actively negotiate their energy and flexibility transactions while offering them full decision making authority [10].

Significant efforts have been made to develop effective energy management methodologies for optimal utilization of demand-side flexibilities to enhance the energy-balance of the grid. For example, the authors in [11], [12] explored consumer engagement plans in DR schemes for peak-load reduction of the residential networks considering user preferences for flexibility support. A consumer-centric DSM scheme is proposed in [13] for residential load control that applies a human behavior modeling approach to identify consumption patterns and demand flexibility potentials of the consumers. The transactive load control methods are presented in [5], [14] for DR schemes to minimize energy cost for the consumers and reduce peak-demand of the grid.

Several studies also presented market-based methods for demand-side flexibility utilization in the local energy balance of the grid. For example, energy trading in the local markets is used in [15], [16] for consumers' cost minimization, and inter-microgrid TE markets are proposed in [17], [18] for the economic energy balance of neighboring microgrids. The integrated local and wholesale TE markets are proposed in [19], [20] that utilize demand-side flexibilities for the efficient and economic energy balance of the grid. An LGO-centric integrated market model is presented in [21] whereby the LGO acts as an aggregator of the demand-side flexibilities and participates in both the day-ahead wholesale market and local energy market. The authors in [22] also used an integrated market model for transactive trading between energy suppliers and grid operators, where consumers' DER units are scheduled in day-ahead by the LGO for an economic energy balance within the local networks. Studies show that market-based approaches can also facilitate LGO to procure demand-side flexibilities for addressing local grid-capacity issues. For example, a local TE market model is presented in [10] where LGO procures consumers' demand and supply flexibility to prevent transformer overloading, and the authors in [23] proposed a local TE market model for local voltage regulations. Hierarchical and nested market models are used in a few studies for effective trading and aggregation of demand-side flexibilities. For example, the authors in [24] proposed a hierarchical real-time electricity market involving LGO, local flexibility aggregators and flexible consumers. Detailed analyses show that the monopolistic method of flexibility management is profitable for demand-side entities whereas game-theoretic approaches favor the LGO [24]. A game-based interaction method is also used in [25] that maximizes welfares of the grid operator, local service providers and consumers in a hierarchical wholesale DR market.

Traditional DR or consumer-centric DSM schemes are profitable for the consumers and enhance the energy-balance of the grid. However, they offer little to no support for the LGO in terms of addressing grid-capacity issues. On the other hand, grid-centric schemes benefit the LGO while limiting consumers' profit and welfare. Inclusion of grid issues in consumer-centric approaches also affect their profitability and can raise privacy concerns if consumers are required to share consumption-related information with grid-entities or aggregators. While offering optimal equilibrium for distributed interactions, the game-theoretic methods also fail to address consumers' privacy issues and often reduce their decision-making authority. In this regard, marker-based methodologies involving transactive trading can offer consumers with full-decision making authority if they are allowed to actively bid for energy or flexibility transactions. Such active bidding also nullifies any privacy concerns as they only required to submit cost-quantity bids to the market entities. However, active bidding for energy or flexibility trading is limited for small-scale residential consumers in most TE models found in the literature. For example, consumers' flexibilities are managed by a third-party transactive aggregator in [7], [17], [18], [20] or microgrid aggregator in [5], [14], [19]. On the other hand, [15], [16], [22] model consumers as price-taker in the TE market. In addition to that, the myopic human behaviors in terms of convenience reservations for appliance usage are not considered in the TE methodologies of [8], [9], [18], [22], [23]. Our previous work in [10] illustrates that active consumer bidding for transactive trading would encourage higher participation in the TE market by increasing their profitability, reducing privacy concerns, reserving their conveniences, and offering them full decision-making authority. However, only local flexibility trading is considered in [10], whereas integrated wholesale and local TE markets [19], [20], [22] would significantly enhance both local and wholesale energy-balance while addressing local and system-level grid issues. The integrated marker models required bottom-up flexibility aggregation and a nested approach would effectively reduce the communication complexity in this regard [26].

To this end, a nested TE market model is presented in this paper for the effective utilization of demand-side flexibilities. The proposed TE market includes local flexibility markets (LFM) at the LV side of the grid where LGO procure active consumers' demand-reduction and energy-supply flexibilities to prevent transformer overloading, and a central wholesale DR market (WSDRM), where a wholesale DR service provider (WDRSP) procures aggregated demand-side flexibilities to minimize wholesale energy price during peak wholesale tariff periods. The demand-side flexibilities are aggregated in nested layers to integrate LFM with WSDRM with feasible communication complexity. A novel biding strategy is proposed for residential consumers with DER to ensure active consumer participation in the TE market. The key contributions of this paper are to:

- design a nested TE market model for integrating LFM and WSDRM, where demand-side flexibilities can be traded for local grid issues (i.e. transformer overloading) in the LFM, and WSDRM utilizes aggregated demand-side flexibilities to minimize wholesale energy price when wholesale energy-balance is subjected to unpredicted peak tariffs,

- develop a novel transactive bidding strategy for the small-scale residential consumers that maximizes profit while considering electricity cost, storage degradation, and thermal discomfort, and
- develop a flexibility trading model for the proposed integrated TE markets to minimize cost (or maximize profits) for all involved stakeholders including active consumers, grid operators, transactive agents, and wholesale DR service provider.

The remainder of this paper is organized as follows: the proposed TE framework is presented in Section II, the mathematical formulations of consumers flexibility bidding and TE market methodology are discussed in Section III, and Section IV respectively, then the simulation studies are discussed in Section V for numerical validation of the proposed method, followed by the conclusion of the paper in Section VI.

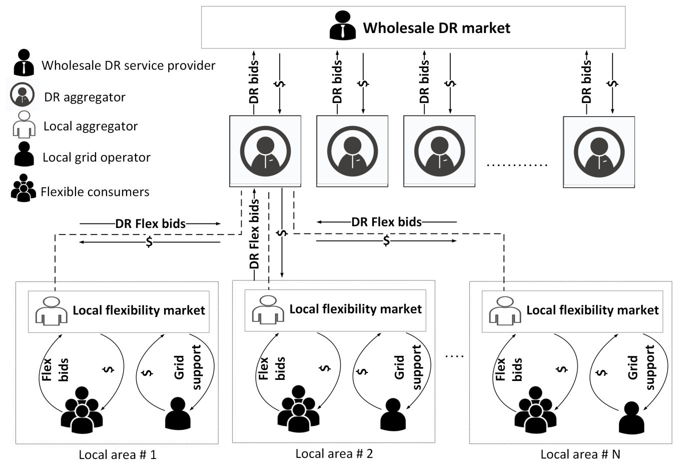

Fig. 1. Overview of the nested transactive market framework.

II. Transactive market framework

The proposed nested TE market framework is illustrated in Fig. 1. At the bottom layer, each local aggregator (LA) coordinates an LFM that provides grid-support services to the LGO. In this paper, the network service area within a distribution transformer is considered as a local area. When aggregated load demand within a local area exceeds beyond the maximum transformer capacity, then the LGO requests for demand-reduction support from the LFM. The LA procures the demand-reduction and energy-supply flexibility of the participating consumers within the local area to provide grid-support service to the LGO. The LA is remunerated for its flexibility-support according to the aging cost of the transformer for overloading. During each flexibility trading interval, the LA broadcasts flexibility requests to the participating consumers within the local area, who then submit flex bids to be traded in the local market. The flex bids of the consumers are quantity-cost transactive bids that include the demand-reduction flexibility of the consumers and the associated costs for the flexibility support. The demand-reduction of a particular consumer can be higher than its consumption indicating energy-supply to the grid. The LA determines the market-clearing tariff for the LFM by maximizing its profit for each trading interval. The consumers are rewarded for their accepted flex bids based on the market-clearing tariff.

On the other hand, the WSDRSP requests DR bids from the participating DR aggregators (DRA) of the WSDRM prior to any wholesale DR events, identified as the scenario when wholesale tariff exceeds a predetermined threshold level. The DRAs notify the consumers for transactive flex bid submission via corresponding LAs. Each LA aggregates the flex bids of the consumers within its cluster and submits an aggregated transactive DR flex bid to their coordinating DRA. The DR flex bids of the LAs includes the step-wise demand reduction flexibility for its local area and required cost (or reward to be given to the consumers) for each demand reduction level. The DRAs aggregate the DR flex bids of their LAs and submit the aggregated DR bids to the WDRSP. The WDRSP clears the WSDRM by minimizing the total DR rewards required for each DR event. The DRAs and LAs distribute the DR reward among the consumers by determining an optimal clearing tariff for their corresponding service area that minimizes total payable reward for the DRAs and LAs while satisfying local grid constraints. As a result, all the consumers in a local area are rewarded at an unique clearing tariff for their accepted flexibility support, which ensures fair distribution of reward.

III. Consumers' flexibility modeling

An optimization-based two-stage scheduling model is proposed for the flexible consumers. In the first stage, consumers' flexible resources are pre-scheduled in day-ahead to minimize cost, whereas consumers' flex bids are determined in the second-stage for real-time TE market by rescheduling the flexible building resources.

A. Pre-schedule model

The pre-schedule model is formulated as a cost-minimization problem to determine the schedule of flexible building resources for the next 24 hours. The consumers are considered to be equipped with three flexible resources - air-conditioners (AC), electrical energy storage (EES) units and electric vehicle (EV) with vehicle to building (V2B) and vehicle to grid (V2G) functionalities. However, the inelastic load demand and on-site DG supply are considered non-controllable and foretasted with reasonable accuracy for the pre-scheduling.

1) Objective function: The pre-scheduling model determines the energy consumption and supply of each consumer $i \in \mathcal{I}$ for the time periods $t \in \mathcal{T}$ of the next day. Considering time varying tariffs for demand and supply of λ^+ and λ^- respectively, the electricity cost can be calculated as:

$$C_{i,t} = (\lambda_t^+ P_{i,t}^+ - \lambda_t^- P_{i,t}^-)\Delta t \quad \forall i, t \tag{1}$$

However, such scheduling often introduces irregular and frequent charge-discharge cycles for storage units and accelerate their cycle-aging. The storage degradation cost can be calculated as:

$$\Phi_{i,t} = \sum_{b \in B} C^R_{b,i} \Psi\left(P^d_{b,i,t}\right) \quad \forall i,t \tag{2}$$

where, $C^R_{b,i}$ is the replacement cost of the storage unit, $b \in \mathcal{B}$ for consumer, i, and $\Psi(P^d)$ is the marginal cycle-aging degradation function for a discharge cycle with P^d kW. In addition to that, flexible operation of AC often introduces thermal discomfort when indoor temperature deviates from the consumer-specified set-points for cost minimization in peak-tariff periods. Such thermal discomfort cost is calculated as:

$$\Omega_{i,t} = \omega_i |\theta_{i,t} - \theta^{set}_{i,t}| \quad \forall i,t \tag{3}$$

where, the coefficient ω_i represents the flexibility of consumer, i regarding deviation of indoor temperature, θ from set-point temperature, θ^{set}.

The pre-schedule model minimizes the electricity cost, storage degradation, and thermal discomfort of the consumers for next day, i.e.:

$$\min \sum_{t \in \mathcal{T}} (C_{i,t} + \Phi_{i,t} + \Omega_{i,t}) \quad \forall i \tag{4}$$

2) Power balance constraint: The power balance constraint for the pre-scheduling model is written as:

$$P^+_{i,t} - P^-_{i,t} = P^{il}_{i,t} + \sum_{b \in \mathcal{B}} \left(P^c_{b,i,t} - P^d_{b,i,t}\right) + P^{ac}_{i,t} - P^g_{i,t} \quad \forall i,t \tag{5}$$

where, inelastic load demand, P^{il} and DG generation, P^g are considered to be known.

3) Indoor temperature constraints: For the flexible operation of AC, a flexible temperature range is considered as:

$$\underline{\theta_{i,t}} \le \theta_{i,t} \le \overline{\theta_{i,t}} \quad \forall i,t \tag{6}$$

According to the isothermal model [10], [15] the thermal equilibrium equation for the building can be written as:

$$\rho V_i C^{th}_i \frac{\partial \theta_{i,t}}{\partial t} = Q^g_{i,t} + \sum_{s \in \mathcal{S}} \beta_{s,i} A_{s,i} (\theta^o_t - \theta_{i,t}) - \kappa_i P^{ac}_{i,t} \, \forall i,t \tag{7}$$

where, Q^g is the internal heat gain, κ is the coefficient of performance (COP) of the AC, and building's heat transfer coefficient, β determines the heat exchange through building surfaces, $s \in \mathcal{S}$.

4) State of charge (SoC) constraints of storage units: The nominal rated charging and discharging of the storage units are considered, where the binary decision variables, $x^c = 1$ indicates charging, $x^d = 1$ for discharging, and $x^c = x^d = 0$ when it is idle. The charge-discharge constraints are written as:

$$P^c_{t,i,b} = x^c_{t,i,b} P^{cn}_{i,b} \quad \forall t,i,b \tag{8}$$

$$P^d_{t,i,b} = x^d_{t,i,b} P^{dn}_{i,b} \quad \forall t,i,b \tag{9}$$

$$\begin{aligned} x^c_{t,i,b} + x^d_{t,i,b} \le 1 \qquad & \forall t \in \mathcal{T}^a_{i,b}, \forall i,b \\ x^c_{t,i,b} + x^d_{t,i,b} = 0 \qquad & \forall t \notin \mathcal{T}^a_{i,b}, \forall i,b \end{aligned} \tag{10}$$

here, $\mathcal{T}^a$ indicates the set of periods when the storage unit is available, which is the same as the set $\mathcal{T}$ for ESS and in case of EV battery it reflects the period when the EV is at home. Therefore, Eq. (10) indicates that both x and y are zero when the storage unit is unavailable, and a particular storage unit can only be charged or discharged at any time when it is available. The changes in the battery state of charge (SoC) can be written as Eq. (11), whereas the SoC-thresholds are imposed by the constraint in Eq. (12).

$$\frac{\partial}{\partial t}(\sigma_{t,i,b}) = \frac{\left(\eta^c_{i,b} P^c_{i,b} + \frac{P^d_{i,b}}{\eta^d_{i,b}}\right) \Delta t}{E^{cap}_{i,b}} \quad \forall t,i,b \tag{11}$$

$$\underline{\sigma_{i,b}} \le \sigma_{t,i,b} \le \overline{\sigma_{i,b}} \quad \forall t,i,b \tag{12}$$

The proposed model also satisfies user preferences in terms of SoC requirement for the EV before a trip, which is ensured by following constraint:

$$\sigma_{b,i,t} \ge \sigma^{set}_{b,i,t} \quad \forall t = T_d \in \mathcal{T}_D, \forall i,b \tag{13}$$

where, $\sigma^{set} = \{\sigma^{set}_{T_1}, \sigma^{set}_{T_2}, ...\sigma^{set}_{T_D}\}$ indicates the consumer-specified SoC requirements before departure at $T_d = \{T_1, T_2, ...T_D\} \in \mathcal{T}_D$. As such SoC requirements are only valid for EV battery, σ^{set} is a null set for ESS.

5) Storage degradation: The cycle-aging storage degradation model presented in [10] is used in this paper to estimate the marginal storage degradation as:

$$\Psi(P) = \frac{\partial \varphi}{\partial P} \times P = \frac{\Delta \varphi}{\Delta \gamma} \times \frac{\partial}{\partial P}(\gamma) \times P \tag{14}$$

where, $\varphi = c_1 \gamma^{c_2}$, γ is the depth of discharge (DoD), and φ is the non-linear DoD stress function for storage degradation specified by constants c_1 and c_2. However, a piece-wise linear model is used in this paper for estimating the storage degradation so that the pre-scheduling optimization problem can be solved in 'off the shelf' solvers within feasible time. The piecewise linearized DOD stress function is written as:

$$\varphi_{l,b,i,t} = \sum_{l \in \mathcal{L}} \left(M_{l,b,i} \gamma^{lin}_{l,b,i,t} + C_{l,b,i} \mu_{l,b,i,t}\right) \quad \forall b,i,t \tag{15}$$

where, the auxiliary optimization variables γ^{lin} and μ determine the active segments of the piece-wise linearized model in Eq. (15), whereas $l \in \mathcal{L}$ indicates its the linear segments with line coefficients M_l and C_l. Only the linear line segment corresponds to the initial DoD of any discharge cycle must be active, which can ensured by the constraint in Eq. (16), whereas the constraints in Eqs. (17) and (18) restrict γ^{lin} within that line segment, and the initial DoD for any discharge cycle is estimated from Eqs. (19) to (21).

$$\sum_{l \in \mathcal{L}} \mu_{l,b,i,t} = x^d_{b,i,t} \quad \forall b,i,t \tag{16}$$

$$\sum_{l\in\mathcal{L}}\gamma^{lin}_{l,b,i,t}=\gamma^{d}_{b,i,t}\quad\forall b,i,t \tag{17}$$

$$\mu_{l,b,i,t}\underline{\gamma^{lin}_{l,d,i}}\leq\gamma^{lin}_{l,b,i,t}\leq\mu_{l,b,i,t}\overline{\gamma^{lin}_{l,d,i}}\quad\forall l,b,i,t \tag{18}$$

$$\gamma^{c}_{b,i,t}+\gamma^{d}_{b,i,t}=\gamma_{b,i,t}=1-\sigma_{b,i,t}\quad\forall b,i,t \tag{19}$$

$$\gamma^{d}_{b,i,t}\leq x^{d}_{b,i,t}\quad\forall b,i,t \tag{20}$$

$$\gamma^{c}_{b,i,t}\leq 1-x^{c}_{b,i,t}\quad\forall b,i,t \tag{21}$$

where, $\underline{\gamma^{lin}_{l,d,i}}$ and $\overline{\gamma^{lin}_{l,d,i}}$ are the initial and final DoD levels in the linear line segment, l. On the other hand, γ^d and γ^c are included as auxiliary optimization variables related to storage DoD, where γ^d is the battery DoD when the storage unit is discharging (as indicated by $x^d_{b,i,t}$), and the variable γ^c indicates its DoD when it is charging.

B. Reschedule model and consumers' flex bids

The flex bids represent the demand reduction flexibility of the consumers in kW and the associated reward rate in \$/kWh. In this paper, a multi-step flex bid is considered where the maximum demand reduction flexibility of a consumer is divided into m steps in cumulative-ascending order. Let, at time $t=t_f$, the participating consumers receive flexibility requests from the coordinating LA, then the flex bids are calculated in following 3 steps:

1) Determine maximum demand reduction ($\Delta P^{total}_{t_f,i}$): The maximum demand reduction of the AC at any given time, ΔP^{ac} is written as in Eq. (22), which depends on the indoor temperature and user-specified maximum temperature threshold of that time. Here, the function $[.]_+$ indicates $[\mathcal{X}]_+=max(\mathcal{X},0)$. Eq. (22) indicates that when the indoor temperature is at the maximum limit, then demand reduction is not possible for the AC as it would violate temperature constraint. On the other hand, when the temperature is lower than the maximum limit, the AC power demand can be reduced to a level sufficient enough to maintain indoor temperature at the maximum allowed limit. On the other hand, the maximum demand reduction flexibility of the storage units, ΔP^{st} depends on their SoC levels according to the pre-schedule and defined as in Eq. (23). Here, the function $[\mathcal{X},\mathcal{Y}]_+$ indicates $max(\mathcal{X},\mathcal{Y})$, and $[\mathcal{X},\mathcal{Y}]_-$ represents $min(\mathcal{X},\mathcal{Y})$. Therefore, Eq. (23) indicates that the charging of a storage unit could be curtailed and can even be allowed to discharge at $t=t_f$ if it does not violate any SoC constraints.

Therefore, the total maximum demand reduction of a consumer, ΔP^{total} at $t=t_f$ can be written as:

$$\Delta P^{total}_{i,t_f}=\Delta P^{ac}_{i,t_f}+\sum_{b\in\mathcal{B}}\Delta P^{st}_{b,i,t_f}\quad\forall t_f\in\mathcal{T},\forall i\in\mathcal{I} \tag{24}$$

2) Reschedule- determine new schedules: For each step increase of the demand reduction level indicated by $m\in\mathcal{M}$, a new schedule is estimated for time periods $t=t_f$ to $t=T$. The reschedule model is also formulated as a minimization problem, which can be written as:

$$\min_{\delta}\sum_{t=t_f}^{T}\left(C_{i,t}+\Phi_{i,t}+\Omega_{i,t}\right)\quad\forall i \tag{25a}$$

$$\text{s.t. }\delta^{total}_{m,i,t_f}=\delta^{ac}_{m,i,t_f}+\sum_{b\in\mathcal{B}}\delta^{st}_{m,b,i,t_f}\leq m\Delta P^{total}_{i,t_f} \tag{25b}$$

$$P^{ac'}_{m,i,t_f}=P^{ac}_{i,t_f}-\delta^{ac}_{m,i,t_f} \tag{25c}$$

$$P^{c'}_{m,b,i,t_f}-P^{d'}_{m,b,i,t_f}=(P^{c}_{b,i,t_f}-P^{d}_{b,i,t_f})-\delta^{st}_{m,b,i,t_f} \tag{25d}$$

$$P^{+}_{m,i,t_f}-P^{-}_{m,i,t_f}=P^{il}_{i,t_f}-P^{g}_{i,t_f}+P^{ac'}_{m,i,t_f}+\sum_{b\in\mathcal{B}}\left(P^{c'}_{m,b,i,t_f}-P^{d'}_{m,b,i,t_f}\right) \tag{25e}$$

$$Eqs.\ (5) to\ (13)\quad\forall t>t_f \tag{25f}$$

$$\delta^{ac}_{i,t_f}\in[0,m\Delta P^{ac}_{i,t_f}],\delta^{st}_{b,i,t_f}\in[0,m\Delta P^{st}_{b,i,t_f}] \tag{25g}$$

where, δ^{ac} and δ^{st} indicate the demand reduction of the AC and storage units respectively. Therefore, the total demand reduction according to the reschedule is δ^{total} and corresponding power for AC and storages at time $t=t_f$ is indicated by $P^{ac'}_m$, $P^{c'}_m$, and $P^{d'}_m$ for the demand reduction level, m. The power balance at t_f is indicated in Eq. (25e), whereas other optimization constraints are the same as the pre-schedule for

$$\Delta P^{ac}_{i,t_f}=\left[P^{ac}_{i,t_f}-\frac{1}{\kappa_i}\left\{Q^{g}_{i,t_f}+\sum_{s\in\mathcal{S}}\beta_{s,i}A_{s,i}(\theta^{o}_{t_f}-\overline{\theta_{i,t_f}})-\rho V_i C^{th}_i\frac{\overline{\theta_{i,t_f}}-\theta_{i,t_f-1}}{\Delta t}\right\}\right]_+\quad\forall t_f\in\mathcal{T},\forall i\in\mathcal{I} \tag{22}$$

$$\Delta P^{st}_{b,i,t_f}=\begin{cases}\left[P^{cn}_{b,i}+P^{dn}_{b,i},\frac{1}{\Delta t}\left(\sigma_{b,i,t_f}-\left[\sigma^{set}_{b,i,t_f},\underline{\sigma_{b,i}}\right]_+\right)\right]_- & \forall t_f\in\mathcal{T},\forall i,b\ \text{ if }\ x^{c}_{b,i,t_f}=1\\ \left[P^{cn}_{b,i},\frac{1}{\Delta t}\left(\sigma_{b,i,t_f}-\left[\sigma^{set}_{b,i,t_f},\underline{\sigma_{b,i}}\right]_+\right)\right]_- & \forall t_f\in\mathcal{T},\forall i,b\ \text{ if }\ x^{c}_{b,i,t_f}=x^{d}_{b,i,t_f}=0\\ 0 & \forall t_f\in\mathcal{T},\forall i,b\ \text{ if }\ x^{d}_{b,i,t_f}=1\end{cases} \tag{23}$$

$$\pi_{m,i,t}=\frac{\sum_{t=t_f}^{T}\left(\left[C'_{m,i,t}-\left(\frac{E^{g'}_{m,i,t}}{E^{g}_{i,t}}\right)C_{i,t}\right]_++\left[\Phi'_{m,i,t}-\sum_{b=1}^{B}\left(\frac{x^{d'}_{m,b,i,t}}{x^{d}_{b,i,t}}\right)\Phi_{i,t}\right]_++\left[\Omega'_{m,i,t}-\left(\frac{P^{ac'}_{m,i,t}\Delta t}{P^{ac}_{i,t}\Delta t}\right)\Omega_{i,t}\right]_+\right)}{\delta^{total}_{m,i,t_f}\Delta t} \tag{26}$$

$t \geq t_f$ as indicated in Eq. (25f). The values of $C_{i,t}$, $\Phi_{i,t}$, and $\Omega_{i,t}$ are calculated according to Eqs. (1) to (3) and Eqs. (14) to (21).

3) Estimate reward rate for demand reduction: In the final step, the required rewards for each incremental demand reduction, δ_m^{total} are estimated according to Eq. (26). Here, $\mathcal{X}'$ indicates the optimal value of $\mathcal{X}$ according to the reschedule model in Eq. (25), i.e.:

$$\mathcal{X}'_{m,i,t_f} = \arg\min Eq.\ (25) \quad \forall m, i, t_f \tag{27}$$

The energy demand/supply from/to the grid is represented by E^g in Eq. (26), i.e.:

$$E^g_{t,i} = \left(P^+_{t,i} - P^-t, i\right) \Delta t \quad \forall t, i \tag{28}$$

The rationale of Eq. (26) is that a consumer should be rewarded any additional electricity cost incurred due to rescheduling for flexibility support. In addition to that, Eq. (26) ensures that a consumer is rewarded any incidental storage degradation and thermal discomfort cost incurred due to reschedule.

IV. TE MARKET MECHANISM

The overall flowchart for the TE markets is illustrated in Fig. 2. The LFM and WSDRM are event-triggered markets, where LFM activates for transformer overloading (i.e. if $P^{tx}_t > \overline{P^{tx}}$) and WSDRM is active for any period when wholesale tariff, π^{ws}_t exceeds a threshold limit, $\overline{\pi^{ws}}$. The corresponding market operators broadcast flexibility requests to the participating consumers for each market interval. The consumers then generate their flex bids by comparing the pre-schedule with a real-time reschedule at that time. Upon receiving step-wise cost-quantity bid functions from the consumers, the market operator of LFM and WSDRM clears the corresponding market by minimizing total profit for them and send dispatch signals to the consumers. The dispatch signal includes the market-clearing tariff, π^* and the selected bid, δ^*_i for each consumer, $i \in \mathcal{I}$. Based on this, the consumers then update their schedule if their flex bids are accepted. For example, out of M demand reduction flex bid steps, if m-th bid is accepted for a consumer i, it shall be rewarded $(\pi^*_t \times \delta_{m,i,t})$\$ for its flexibility support, where π^*_t is the market-clearing tariff at t for the local area the consumer i belongs to. This is to be noted that, the market-clearing mechanisms ensure that $pi^*_t > pi_{i,m,t}$ to guarantee profits for consumers' flexibility support. If a flex bid for a particular consumer is accepted, then the reschedule from the corresponding bid-level (as shown in Eq. (25)) is used as the updated schedule. The updated schedule is later used as a pre-schedule for flex bid calculation for any subsequent transactions. The market-clearing mechanisms for the LFM and WSDRM are discussed in the following sections.

A. Local flexibility market (LFM)

LA coordinates the flexible consumers within its cluster and manages the LFM. It procures demand reduction flexibility of the consumers and provides grid-support service to the LGO. We only consider transformer overloading prevention in this paper, however, other grid-assistance services (e.g. local voltage support) can also be incorporated into the proposed TE model. The LA receives a reward for the flexibility service based on the transformer aging cost due to overloading.

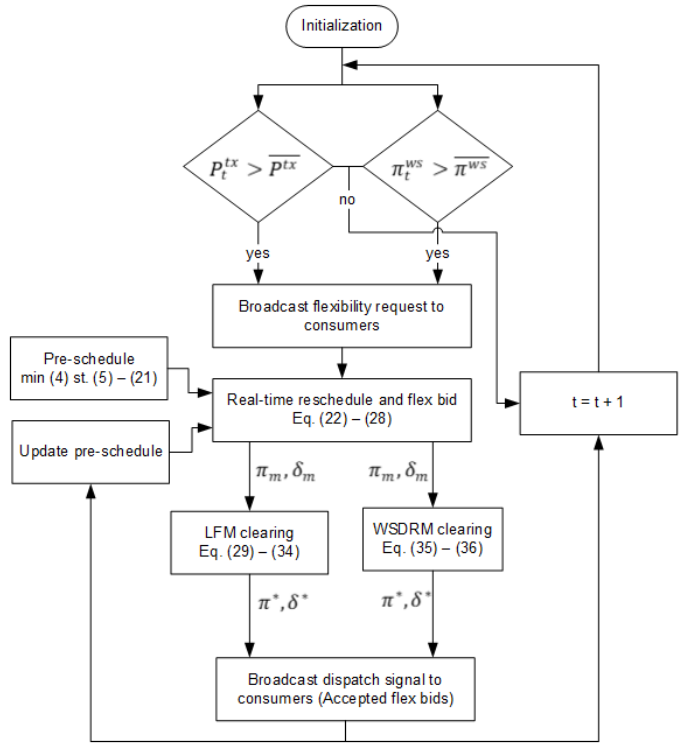

Fig. 2. Flowchart of the TE markets.

1) Transformer aging cost for overloading: The aging cost of transformer can be calculated according to the hottest-spot temperature model of IEEE standard C57.91-2011 [27], which specifies hottest-spot temperature, θ^H as:

$$\theta^H_t = \theta^o_t + \Delta\theta^{RT} \left[\frac{K^2_t R + 1}{R + 1}\right] + \Delta\theta^{RH} K^2_t \quad \forall t \tag{29}$$

here, R is the ratio of rated-load loss to the no-load loss. The rated-load temperature rise beyond the ambient temperature, θ^o in the tap-oil and winding hottest spot are represented by $\Delta\theta^{RT}$ and $\Delta\theta^{RH}$ respectively, whereas for a maximum transformer capacity of $\overline{P^{tx}}$ kW, the load factor, K can be written as:

$$K_t = \frac{P^{tx}_t}{\overline{P^{tx}}} \tag{30}$$

$$P^{tx}_t = \sum_{i \in \mathcal{I}} \left(P^+_{i,t} - P^-_{i,t}\right) + \sum_{j \in \mathcal{J}} P^{il}_{j,t} \quad \forall t \tag{31}$$

where, P^{tx} is the aggregated transformer load, and P^{il}_j is the power demand of the traditional consumers $j \in \mathcal{J}$, without any flexible resources.

The transformer-aging acceleration factor, $\mathcal{A}$ can be expressed as a function θ^H as [27]:

$$\mathcal{A}_t = \exp^{\left[\frac{15000}{383} - \frac{15000}{\theta^H_t + 273}\right]} \quad \forall t \tag{32}$$

Therefore, considering a transformer with replacement cost of C^{tx} and normal insulation life of N hours, the overloading cost can be calculated as:

$$\Gamma_t = C^{tx}\frac{\mathcal{A}_t \Delta t}{N} \quad \forall t \tag{33}$$

2) Market clearing of LFM: The market-clearing problem of the LA is formulated as an optimization model to maximize profit as follows:

$$\max_y \left(\Gamma_t - \pi_t^* \sum_{m,i} y_{m,i,t}\delta_{m,i,t}^{total}\Delta t \right) \quad \forall t \tag{34a}$$

$$\text{s.t.} \sum_m y_{m,i,t} \leq 1 \quad \forall i,t \tag{34b}$$

$$\pi_t^* = \max\left\{y_{m,i,t} \times \pi_{m,i,t}\right\} \quad \forall t \tag{34c}$$

$$\sum_{m,i} y_{m,i,t}\delta_{m,i,t}^{total} \geq \Delta P_t^{tx} = \left[P_t^{tx} - \overline{P_t^{tx}}\right]_+ \quad \forall t \tag{34d}$$

here, the first part of the objective function in Eq. (34a) is the rewards received from the grid operator and the second part is the flexibility procurement cost. Therefore, it maximizes the profits for the local aggregator. The binary variable y indicates the accepted flex bids of the consumers that leads to maximum profits for the aggregator, and the constraint in Eq. (34b) ensures that maximum one bid is selected from a particular consumer. The market-clearing price, π^* is considered as the maximum reward-tariff from the accepted flex bids (as indicated in Eq. (34c)) to maintain fair distribution of flexibility reward among consumers. The constraint in Eq. (34d) ensures that total procured demand reduction flexibility is at least the same as the transformer overloading.

B. Wholesale demand response market (WSDRM)

During a DR event, the WDRSP requests demand reduction flexibilities to the participating DRAs ($k \in \mathcal{K}$), who then broadcast flex bid requests to the participating consumers ($i \in \mathcal{I}$) via LAs ($n \in \mathcal{N}$). Consumers submit their flex bids according to the methodology presented in Section III. Consumers' flex bids are aggregated in two-stages, first locally by LAs and then centrally by the DRAs, who then submit aggregated transactive DR bids to the WDRSP. The WSDRM is cleared by WDRSP with the main objective of minimizing the DR rewards for the required demand reduction. Therefore, the objective of WDRSP can be written as:

$$\min_z \pi_t^{DRA} \sum_{m,k} z_{m,k,t}\delta_{m,k,t}^{agg}\Delta t \quad \forall k \tag{35a}$$

$$\text{s.t.} \sum_m z_{m,k,t} \leq 1 \quad \forall t,k \tag{35b}$$

$$\sum_{m,k} z_{m,k,t}\delta_{m,k,t}^{agg} \geq \Delta P_t^{DR} \quad \forall t \tag{35c}$$

$$\pi_t^{DRA} = \max\{z_{m,k,t} \times \pi_{t,m,k}\} \tag{35d}$$

here, the binary variables z determine the accepted DRA bids from the aggregated bids, $\delta_{m,k,t}^{agg}$ for DRA, $k \in \mathcal{K}$, and ΔP_t^{DR} is the required demand reduction for the DR event at time, t. Eq. (35b) ensures that maximum accepted bid for a DRA is one, and the DR rewards are distributed fairly at π_t^{DRA} ¢/kWh among accepted DRAs according to Eq. (35d).

Once the whole-sale DR market is cleared, the DRAs (whose DR bids are accepted for demand reduction) distribute the required demand reduction, $\delta_{t,k}^*$ among the participating consumers by minimizing the total rewards for consumers' flexibility subject to local grid constraints, which can be written as:

$$\min_y \sum_n \pi_{n,k,t}^{LA} \sum_{m,i} y_{m,i,n,k,t}\delta_{m,i,n,k,t}^{total}\Delta t \quad \forall t,k \tag{36a}$$

$$\text{s.t.} \sum_m y_{m,i,n,k,t} \leq 1 \quad \forall t,i,n,k \tag{36b}$$

$$\sum_{m,i,n} y_{m,i,n,k,t}\delta_{m,i,n,k,t}^{total} = \sum_m z_{m,k,t}\delta_{m,k,t}^{agg} \; \forall t,k \tag{36c}$$

$$\pi_{n,k,t}^{LA} = \max\{y_{m,i,n,k,t} \times \pi_{m,i,n,k,t}\} \quad \forall t,n,k \tag{36d}$$

$$P_{n,k,t}^{tx} - \sum_{m,i} y_{m,i,n,k,t}\delta_{m,i,n,k,t}^{total} \geq \underline{P_{n,k}^{tx}} \quad \forall t,n,k \tag{36e}$$

here, the binary variables y indicates the accepted flex bids of the consumers for the DR event, and π^{LA} is the clearing tariff for the flexibility support for the consumers within a LA. Eq. (36c) is the power balance equation that distributes the required demand reduction of a DRA within its LAs.

V. Numerical validation

A. Simulation setup

The proposed methodology is validated via simulation studies considering different participation levels of residential consumers. The following sections discuss the input parameters and setup for the case studies used to numerically validate the proposed method.

1) Market parameters: For the nested TE market, each local area is considered to be consist of 100 consumers, who are supplied by a 400 kVA distribution transformer and coordinated by an LA. A total of 100 such LAs are considered to be coordinated by a DRA, and 100 identical DRAs are considered resulting in a total consumer of 1 Million. All the consumers are considered to be offered the same time-varying tariffs for demand and supply, which are shown in Fig. 3. The time-of-use (TOU) demand tariff and feed-in-tariff (FIT) used in this paper are estimated from the average tariffs offered by the major retailers in New South Wales, Australia [10].

2) Consumer parameters: Synthetic profiles of consumers' inflexible load demand are generated by applying appropriate distribution fitting to the Smart-Grid Smart-City (SGSC) customer trial data [28]. It is assumed that non-flexible consumers (who do not have any flexible loads or resources) do not have any incentives to participate in the TE market. Therefore, only the flexible consumers are considered to be participating in the proposed TE market. The flexible consumers are considered to be equipped with a rooftop solar PV unit, an EV with V2G and V2B functionality, an ESS, and an AC. The PV units are considered with a maximum installed capacity of 1.5-6 kW$_\text{p}$, and their generation profiles are generated from the distribution fitting of roof-top solar PV data in [29].

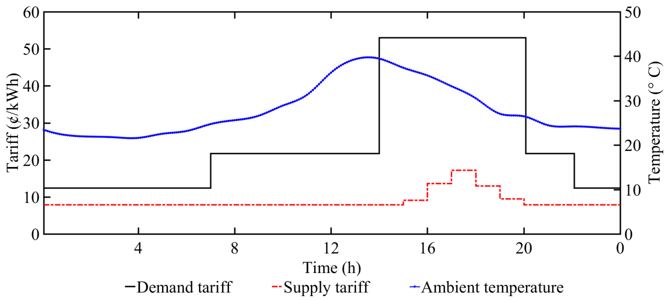

Fig. 3. Simulation input data (tariff and temperature profiles.)

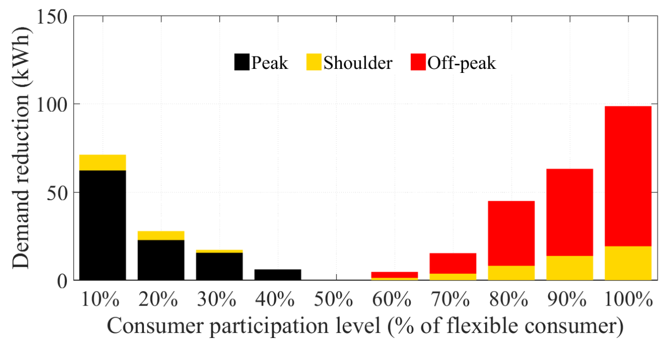

Fig. 4. Required demand reduction for transformer overloading.

The EV batteries are considered with 18-100 kWh maximum capacity, with rated charge-discharge power ranging from 2.8-6.6 kW and round-trip efficiencies of 90-95%. The EV availability, SoC requirements before departure, and energy used for daily commute are approximated from the SGSC EV trail data [30]. The ESS units are considered with 4-10 kWh storage capacity, 1-4 kW rated charge-discharge power, and the charge-discharge efficiencies are considered as 95-98%. The capacities of ACs are considered as 2.5-6 kW with COP ranging from 2.5-3. The consumer buildings are considered with 120-250 m^2 effective floor area in 1-2 levels representing typical detached and semi-detached suburban houses of the region. The thermal parameters of the buildings are estimated from [15] considering different building surface areas and occupancy levels. The storage replacement costs are considered as 500 $/kWh for both ESS and EV battery. For the piecewise linear model of Eq. (15), 10 linear line segments are found sufficient as it gives less than 0.001 root-mean-squared-error (RMSE) for $c_1 = 5.024E-4$ and $c_2 = 2.03$ [10], [15].

3) Case studies setup: The simulations are run with discrete periods of 5 min, which is the same as the bidding period of regional wholesale market. The simulations are run for a hot summer day (14 January 2016), and the outdoor temperature profiles for the day is shown in Fig. 3. Due to the higher mid-day temperature, the wholesale electricity tariff reached a record peak on this specific day. For this reason, this specific day is used for simulation studies to evaluate the effectiveness of the proposed method in an extreme situation.

Based on the input parameters the pre-schedule is first generated for the flexible consumers, and when the aggregated transformer load for an LA exceeds its rated capacity, the participating consumers within the LA are asked to submit their flex bids. Consumers' flex bids are generated by comparing the real-time reschedule with their pre-schedule. Then the LA clears the LFM, sends the market-clearing signal to the consumers, and the consumers update their schedule accordingly. For the LFM, the transformer replacement cost is considered as 30000$ AUD [31] with an insulation life of 15 years [32]. The transformer parameters R, θ^{RT}, and θ^{RH} are considered as 6, 45° C, and 35° C respectively [32], [33].

On the other hand, the DRAs aggregates consumers' flex bids and submit aggregated DR bids to WSDRSP during wholesale DR events WSDRSP clears the WSDRM, and the DR rewards are distributed to the DRAs, LAs and consumers according to methodology discussed in Section IV-B.

Matlab distribution fitting toolbox is used to generate the distributions of datasets in [28]–[30], which is then used to generate profiles for 1 Million consumers. The flex bids for the WSDR event are also generated in a similar way from the simulated datasets of 10000 consumers. All the optimization problems are formulated as mixed-integer programming (MIP) problems in General Algebraic Modeling System (GAMS) and solved using Baron solver with an absolute and related optimality gap of 0. GAMS Data Exchange (GDX) is used to interface between Matlab and GAMS. The optimization problems for consumers' flex bidding took less than 1 second and none of the market-clearing optimization problems took more than 2 seconds on an Intel Core i7 3.40 GHz computer with 16 GB of RAM.

Different case studies are conducted by running the simulations of the LFM and WSDRM for different participation levels of consumers. The consumer participation level represents the percentage of the total consumers within the area that participate in the TE market. It is noteworthy that only flexible consumers are considered to be participating in the TE markets. Therefore, consumer participation levels also indicate the percentage of flexible consumers to total consumers.

B. Results of local flexibility trading

The simulation results of the local flexibility trading for transformer overloading of a local area are discussed in this section. The demand for non-flexible consumers is considered known and estimated from the SGSC data [28]. On the other hand, the power profiles for flexible consumers (including consumption and grid-supply) are calculated according to the pre-schedule model discussed in Section III-A based on the input data discussed in Section V-A. The aggregated demand for the local area is then calculated and the required demand reduction, ΔP_t^{tx} is calculated according to Eq. (34d).

Fig. 4 illustrates the total required demand reduction to prevent transformer overloading for the whole day with different percentages of flexible consumers within the local area. It can be seen that the required demand reduction decreases as the consumer participation level increases from 10% to 50%, however, beyond that, it starts increasing and eventually reaches almost 100kWh for 100% of consumer participation level. It is to be noted that the consumer participation level also indicates the percentage of flexible consumers. The flexible consumers utilize the demand shifting flexibility of AC and storage units (including ESS and EV battery) to minimize energy consumption during peak hours. As a result, Fig. 4 indicates that the transformer overloading decreases in peak-tariff hours as the percentage of flexible consumers increases. On the other hand, a higher percentage of flexible consumers result in more transformer overloading in off-peak tariff hours as the flexible consumers schedule their EV charging in off-peak hours to minimize electricity costs. A few instances of transformer overloading are also noticed in shoulder tariff periods. For a lower percentage of flexible consumers, these shoulder-period overloading instances are due to inflexible AC consumption of non-flexible consumers during mid-day. However, as the flexible consumers increase in number the AC consumption during mid-day is slightly reduced due to the flexible operation of AC. As a result, nil or negligible overloading instances are noticed during mid-day for flexible consumers' percentage of 30% to 50%. However, as it exceeds 60% a few overloading instances were noticed in the second shoulder period (20 - 22h) due to EV charging as most EVs arrive home by this time and start charging once the peak-tariff periods passed.

It can also be seen that the required demand reduction is zero for this LA when 50% of the consumers have flexible resources. It can vary for different LAs and also depends on the consumers' demand used for simulation studies. However, it gives an insight that the impact on the transformer overloading can be minimized if there is an even distribution of flexible and non-flexible consumers. This is because the DER units and flexible loads of flexible consumers in this case help reduce the aggregated peak demand of the network. However, for lower penetration levels of DER and flexible loads transformer can be overloaded, especially during peak-tariff periods as non-flexible consumers consume more during the evening when the tariff is at its peak. On the other hand, higher adoption levels of DER and flexible loads can effectively prevent demand-peaks during peak-tariff periods due to optimized scheduling, however, it can often cause rebound peaks when electricity is cheaper.

This required demand reduction is procured in the LFM by utilizing consumers' flexibility. The distribution of consumers' reward for their support are illustrated in Fig. 5 along with their demand reduction or energy-supply support in kWh. In case of lower participation levels, fewer consumers are providing support, therefore, the average support per consumer is higher compared to the case of higher consumer participation levels as more consumers are providing support in these cases making the average support per consumer lower. As a result, it can be seen that consumers receive a comparatively higher reward on-average when only 10% of consumers participate in the TE market as the market-clearing tariff is higher in this case due to fewer available flex bids. On the other hand, for the consumer participation level of 20% to 100%, their reward is proportional to the total required demand reduction.

The overall profits for all involved stakeholders of the LFM are shown in Fig. 6. It can be seen that the transformer overloading cost (solid red line) and the total consumer

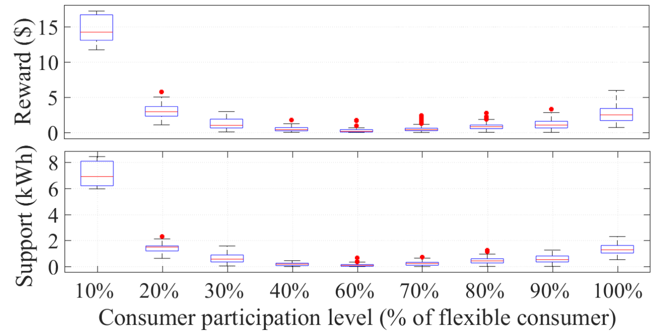

Fig. 5. Distribution of consumers' reward and associated flexibility support.

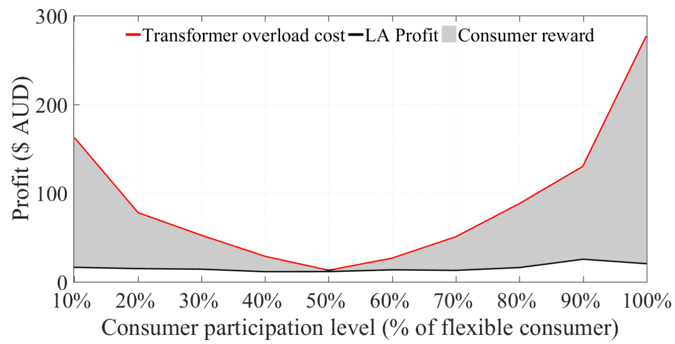

Fig. 6. Overall profit of local flexibility trading.

rewards (indicated by gray fill) are proportional to transformer overloading. On the other hand, the difference between these two is the profit for the LA, which is 12-26$ depending on consumer participation level.

Figs. 5 and 6 illustrate that the median reward rate of an average consumer is 1.5-2.1 $/kWh, which is 10-14 times higher than the existing peak-FIT and 2.8-4 times higher than the peak-TOU tariff. The simulation results also indicate that the proposed LFM methodology would allow the LGO to prevent transformer overloading at a lower cost than the transformer aging cost if the LGO directly procures consumers' flexibility. On the other hand, when the LA coordinates the LFM, it receives at up to 26$/day, while LGO's flexibility procurement cost never exceeds the transformer aging cost even when 100% of the consumer buildings are equipped with EVs. Therefore, it can be argued that the proposed LFM methodology provides significant profits to all the involved stakeholders.

C. Results of wholesale DR trading

The wholesale energy price for the region peaked at 5,022.74$/MWh for the period 13.30h to 14.00h on the 14th of January, 2016 [34], whereas the weekly volume-weighted average wholesale price of that week were 87$/MWh for the region [35]. The main reasons behind this high price peak are higher AC demand due to extreme heat, and unplanned outage of a 344MW generation unit [34]. The cheaper generators took 30min to ramp-up and provide necessary generation, therefore, the dispatch price reduced below average after 14h [34]. Therefore, the case studies were conducted for 6 dispatch periods between 13.30h to 14.00h to evaluate the

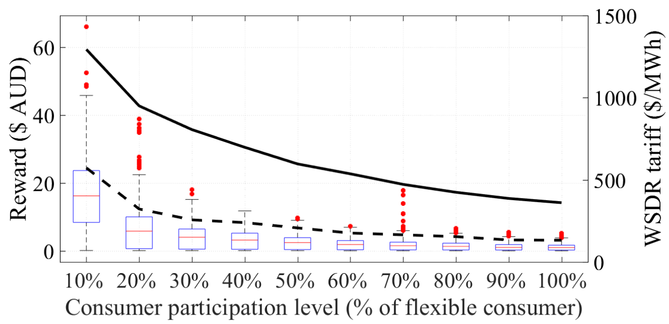

Fig. 7. Average WSDRM tariff and distribution of consumer reward for 6 dispatch periods between 13.30h to 14.00h on 14 January, 2016.

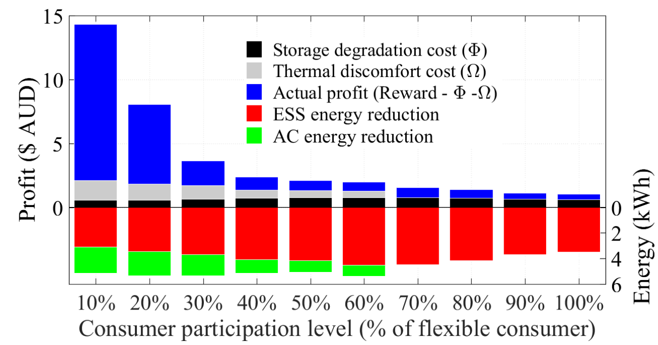

Fig. 8. Comparison between reward and flexibility support of an average consumer in the WSDRM

effectiveness of the proposed method. Determining flex bids for 1 Million consumers for 6 dispatch periods would be highly time consuming. Therefore, the flex bids are generated for the consumers coordinated by a DRA (a total of $100 \times 100 = 10000$ consumers) for the 6 dispatch periods. Then their distributions are used to scale up for all 1 Million consumers to reduce computation time.

Fig. 7 depicts the wholesale DR tariff for procuring 344MW of generation shortage from the proposed TE market. The tariffs represented by the solid black line indicate the average WSDRM clearing price for the 6 dispatch periods. Fig. 7 indicates that the shortage generation can be purchased at one-fourth of the wholesale price with just 10% of consumer participation in the TE-based DR market. Moreover, the tariff for procuring the shortage generation decreases as consumer participation level increases, and it drops below 400$/MWh when 1 Million consumers participate in the proposed TE market, which represents less than half of the total residential consumer of the region. On the other hand, this shortage generation can be bought cheaper when consumers' flexibilities are directly procured by the WDRSO, as indicated by the dashed black line in Fig. 7. The DR tariff drops to about one-third in this case, however, this comes with additional communication complexity and higher infrastructure investment cost as the WDRSO needs to coordinate and directly communicate with a large number of consumers [26]. On the other hand, the distribution of rewards received by the consumers for their flexibility support during this DR event is also shown in Fig. 7, which expectedly decreases as consumer participation level increases.

The DR reward for an average consumer is compared with its flexibility support in Fig. 8. The positive bars in the figure indicate the consumer's reward in $, whereas the negative bars represent its net energy reduction (including energy supply) for the 6 dispatch periods between 13.30h to 14.00h. The portion of energy reductions from the AC and storage units are distinguished by different colors in the figure, whereas the received reward is broken down into degradation cost for storage units, penalty cost for thermal discomfort, and the actual profit of flexibility support, each represented by different colors. The outdoor temperature is too high during 13.30h to 14.00h, therefore, the thermal discomfort per kWh AC energy reduction is higher compared to the degradation cost per kWh energy reduction (or supply) from the storage units. Therefore, the proposed bidding methodology bids higher rewards for AC energy reduction compared to the energy reduction (or supply) from the storage units. Due to fewer flex bids for lower consumer participation levels, higher-priced bids are accepted to provide the necessary support, therefore, both the AC and storage units are selected for flexibility support in such cases. Consequently, it can be noticed that the consumer received a higher reward compared to kWh support for lower consumer participation levels. However, as the consumer participation level increases beyond 60%, the available flex bids become more than the required kWh support, therefore only lower-price bids are accepted. As a result, the consumer received less reward in such cases, and only the storage units are selected for energy reduction (supply) in such situations. Nonetheless, results illustrate that the consumer achieves more profit compared to net storage degradation and thermal discomfort cost by participating in the TE market, and the net profit is always higher than the energy-supply incentives according to existing FIT and TOU tariffs.

D. Discussion

An integrated demand-side flexibility trading model is presented in this paper based on a nested TE market architecture. Compared to traditional DR or DSM strategies, the proposed TE market-based framework offers an economic flexibility-trading method for all involved stakeholders. It maximizes the welfare (or minimizes cost) for both the LGO and participating consumers while providing them with full-autonomy. The proposed market framework reserves consumers' privacy as they only share their flexibility bids with the associated cost. Contrary to game-theoretic methodologies in [18], [24], [25] and most TE-based models found in the literature [5], [7], [14], [17]–[20], the flexibility bidding strategy of this paper offers the consumers with full decision-making authority by allowing them to actively bid for transactive trading. Unlike [5], [7], [14]–[18], [18]–[20], [22], [24], the proposed bidding strategy allows the consumers to act as a price-giver thereby encourages more consumer participation and increases their profitability. In addition to that, the single bidding- and clearing-based market operation of the proposed method requires less communication between market participants compared to iterative market-settlement of game-theoretic models in [18],

[25]. Moreover, the mixed-integer programming (MIP)-based market-clearing of this paper can be solved using 'off the shelf' optimization solvers within feasible time. Besides, it can be easily implemented in embedded devices and incorporated into a residential energy management system for real-world applications.

The efficacy of the proposed method is validated via detailed numerical studies and analyses considering various consumer-participation levels in the proposed TE market. Consumer participation is highly affected by various socio-economic and environmental factors, such as potential economic incentives, peer-pressure, caring for green energy, and so on [36]. Therefore, consumer-participation levels tend to drop as potential financial gain decreases in reactive methodologies, where consumers react to reward or incentive signal forwarded by grid entities (or market) [11], [36]. However, the proposed bidding strategy of this paper allows consumers to bid pro-actively the reward for their potential flexibility support. The flexibility bids are modeled as multi-step price-quantity bids indicating different levels of demand-reductions with associated asking reward. The asking reward of a particular consumer for a specific flexibility support level (i.e. demand reduction) is calculated according to Eq. (26), which ensures that the asking reward is always higher than the additional incurred (if any) electricity cost, storage degradation, and thermal discomfort. Therefore, it is always economically beneficial for a consumer even if its lowest bid is accepted in the market. In addition to that, as indicated in Eqs. (34c) and (35d), the market-clearing prices are set at the highest asking reward among the accepted flex bids to ensure a fair distribution of reward among consumers, whose flexibilities are activated by the market operators for addressing transformer overloading or wholesale price-spikes. Therefore, the proposed market mechanism of the proposed paper increases the profitability of the participating consumers, thereby influencing their active participation.

Case studies also indicate that the flexibility procurement is more economical from the market's or grid operator's perspective with higher consumer participation levels. This is mainly because of the availability of economic flexibility options with higher participation of consumers. The case studies in Sections V-B and V-C were conducted for a summer day, therefore, the flexibility support by curtailing AC power consumption would lead to higher thermal discomfort for the consumers compared to the storage degradation associated with the same demand-reduction (or supply increase by discharging) from storage units. Therefore, the first few levels in the consumers' flex bids represent potential flexibility support from storage units, and they only bid to curtail AC consumption if it does not violate thermal constraints of Eqs. (6) and (7). However, the asking reward of the consumers is higher for demand-reduction levels with AC power curtailment. As a result, when fewer consumers participate in the TE markets, then their higher demand-reduction levels are activated (i.e. higher flexibility support required from each consumer to meet the market objectives), which requires expensive flexibility-support from AC. On the other hand, as the number of consumers increases, their flexibility support from storage units is sufficient to meet the market demand, hence, an average consumer receives less reward as indicated in Fig. 7. However, their rewards still exceed thermal discomfort and storage degradation as shown in Fig. 8.

VI. Conclusion

This paper presents a nested TE market framework for optimal utilization of demand-side flexibility of the residential consumers. Optimal bidding strategy is presented for the residential consumers with DER and flexible loads that minimizes energy cost, storage degradation, and thermal discomfort. Optimization-based market models are developed to trade demand-side flexibility in a nested TE market for addressing transformer overloading and reducing wholesale price peaks when system-level supply is jeopardized. Detailed simulation studies indicate that the proposed method can economically prevent the transformer overloading irrespective of consumer participation levels. Simulation results also illustrate that the demand-side flexibility trading of the proposed methodology is more economic than the wholesale price during the unpredicted and unexpected outage of generation units or excess demand. Moreover, the proposed bidding strategy allows the consumers to trade their flexibility at a higher rate compared to existing FIT or TOU of the regional retailers while considering their thermal discomfort and storage degradation for the flexibility support.

However, the interaction and competition among the aggregators are considered out of the scope of this paper, and the actual wholesale tariff reduction is not quantified as it would require a rigorous bidding model of wholesale suppliers. Besides, the consumer engagement in such a TE market can be largely influenced by many socio-economic factors other than financial gains. These will be considered in future researches by the authors. The proposed market framework is scalable, therefore, another interesting avenue for future research can be integration of other grid-assistance services into the market framework, such as local voltage violation support and ancillary grid services.

References

[1] E. Veldman, M. Gibescu, H. J. Slootweg, and W. L. Kling, "Scenario-based modelling of future residential electricity demands and assessing their impact on distribution grids," *Energy Policy*, vol. 56, pp. 233 – 247, 2013.

[2] O. Ellabban and H. Abu-Rub, "Smart grid customers' acceptance and engagement: An overview," *Renewable and Sustainable Energy Reviews*, vol. 65, pp. 1285 – 1298, 2016.

[3] H. T. Haider, O. H. See, and W. Elmenreich, "A review of residential demand response of smart grid," *Renewable and Sustainable Energy Reviews*, vol. 59, pp. 166 – 178, 2016.

[4] B. P. Esther and K. S. Kumar, "A survey on residential demand side management architecture, approaches, optimization models and methods," *Renewable and Sustainable Energy Reviews*, vol. 59, pp. 342 – 351, 2016.

[5] H. Hao, C. D. Corbin, K. Kalsi, and R. G. Pratt, "Transactive Control of Commercial Buildings for Demand Response," *IEEE Trans. Power Syst.*, vol. 32, no. 1, pp. 774–783, 2017.

[6] "GridWise Transactive Energy Framework version 1," Tech. Rep., 2015. [Online]. Available: https://tinyurl.com/gwac15

[7] "Pacific Northwest Smart Grid Demonstration Project: Technology Performance Report Volume 1: Technology Performance," Tech. Rep., 2015. [Online]. Available: https://tinyurl.com/PNW-SGDP

[8] "Pacific Northwest GridWise(TM) Testbed Demonstration Projects Part I . Olympic Peninsula Project," Tech. Rep., 2007. [Online]. Available: https://tinyurl.com/pnnl07

[9] S. E. Widergren, K. Subbarao, J. C. Fuller, D. P. Chassin, A. Somani, M. C. Marinovici, and J. L. Hammerstrom, "AEP Ohio gridSMART demonstration project real-time pricing demonstration analysis," Tech. Rep. February, 2014.

[10] M. S. H. Nizami, M. J. Hossain, and E. Fernandez, "Multi-agent based transactive energy management systems for residential buildings with distributed energy resources," *IEEE Transactions on Industrial Informatics*, 2019.

[11] N. U. Hassan, Y. I. Khalid, C. Yuen, and W. Tushar, "Customer engagement plans for peak load reduction in residential smart grids," *IEEE Transactions on Smart Grid*, vol. 6, no. 6, pp. 3029–3041, 2015.

[12] N. U. Hassan, Y. I. Khalid, C. Yuen, S. Huang, M. A. Pasha, K. L. Wood, and S. G. Kerk, "Framework for minimum user participation rate determination to achieve specific demand response management objectives in residential smart grids," *International Journal of Electrical Power & Energy Systems*, vol. 74, pp. 91 – 103, 2016.

[13] N. Ahmed, M. Levorato, and G. P. Li, "Residential consumer-centric demand side management," *IEEE Transactions on Smart Grid*, vol. 9, no. 5, pp. 4513–4524, 2018.

[14] S. Behboodi, D. P. Chassin, N. Djilali, and C. Crawford, "Transactive control of fast-acting demand response based on thermostatic loads in real-time retail electricity markets," *Applied Energy*, vol. 210, pp. 1310 – 1320, 2018.

[15] M. S. H. Nizami, M. J. Hossain, B. M. R. Amin, and E. Fernandez, "A residential energy management system with bi-level optimization-based bidding strategy for day-ahead bi-directional electricity trading," *Applied Energy*, vol. 261, 2020.

[16] A. S. Gazafroudi, J. Soares, M. A. F. Ghazvini, T. Pinto, Z. Vale, and J. M. Corchado, "Stochastic interval-based optimal offering model for residential energy management systems by household owners," *International Journal of Electrical Power & Energy Systems*, vol. 105, pp. 201 – 219, 2019.

[17] H. S. V. S. Kumar Nunna and D. Srinivasan, "Multi-Agent based Transactive Energy Framework for Distribution Systems with Smart Microgrids," *IEEE Trans. Ind. Informat.*, vol. 13, no. 5, pp. 2241 – 2250, 2017.

[18] Y. Liu, H. B. Gooi, Y. Li, H. Xin, and J. Ye, "A secure distributed transactive energy management scheme for multiple interconnected microgrids considering misbehaviors," *IEEE Transactions on Smart Grid*, 2019.

[19] F. Lezama, J. Soares, P. Hernandez-Leal, M. Kaisers, T. Pinto, and Z. Vale, "Local energy markets: Paving the path toward fully transactive energy systems," *IEEE Transactions on Power Systems*, vol. 34, no. 5, pp. 4081–4088, Sep. 2019.

[20] P. Paudyal, P. Munankarmi, Z. Ni, and T. M. Hansen, "A hierarchical control framework with a novel bidding scheme for residential community energy optimization," *IEEE Transactions on Smart Grid*, vol. 11, no. 1, pp. 710–719, Jan 2020.

[21] S. Bahramara, P. Sheikhahmadi, A. Mazza, G. Chicco, M. Shafie-khah, and J. P. S. Catalão, "A risk-based decision framework for the distribution company in mutual interaction with the wholesale day-ahead market and microgrids," *IEEE Transactions on Industrial Informatics*, vol. 16, no. 2, pp. 764–778, 2020.

[22] Y. K. Renani, M. Ehsan, and M. Shahidehpour, "Optimal transactive market operations with distribution system operators," *IEEE Transactions on Smart Grid*, vol. 9, no. 6, pp. 6692–6701, Nov 2018.

[23] P. H. Divshali, B. J. Choi, and H. Liang, "Multi-agent transactive energy management system considering high levels of renewable energy source and electric vehicles," *IET Generation, Transmission & Distribution*, vol. 11, no. 15, pp. 3713–3721, 2017.

[24] A. S. Gazafroudi, M. Shafie-Khah, F. Prieto-Castrillo, J. M. Corchado, and J. P. S. Catalão, "Monopolistic and game-based approaches to transact energy flexibility," *IEEE Transactions on Power Systems*, vol. 35, no. 2, pp. 1075–1084, 2020.

[25] M. Yu and S. H. Hong, "Incentive-based demand response considering hierarchical electricity market: A stackelberg game approach," *Applied Energy*, vol. 203, pp. 267 – 279, 2017.

[26] K. Moslehi and A. B. R. Kumar, "Autonomous resilient grids in an iot landscape vision for a nested transactive grid," *IEEE Transactions on Power Systems*, vol. 34, no. 5, pp. 4089–4096, Sep. 2019.

[27] "IEEE Guide for Loading Mineral-Oil-Immersed Transformers and Step-Voltage Regulators," *IEEE Std C57.91-2011 (Revision of IEEE Std C57.91-1995)*, pp. 1–123, March 2012.

[28] Smart-Grid Smart-City (SGSC) Customer Trial Data. [Online]. Available: https://tinyurl.com/sgsccus

[29] Ausgrid solar home electricity data. [Online]. Available: https://tinyurl.com/ausgridsh

[30] Smart-Grid Smart-City (SGSC) EV Trial Data. [Online]. Available: https://tinyurl.com/sgscev

[31] Endeavour Engergy, "Network Price List: Unregulated Network Charges 2015-2016," July 2015. [Online]. Available: https://tinyurl.com/nwprice16

[32] "IEEE Standard for General Requirements for Liquid-Immersed Distribution, Power, and Regulating Transformers," *IEEE Std C57.12.00-2010 (Revision of IEEE Std C57.12.00-2006)*, pp. 1–70, Sep. 2010.

[33] H. Pezeshki, P. J. Wolfs, and G. Ledwich, "Impact of high pv penetration on distribution transformer insulation life," *IEEE Transactions on Power Delivery*, vol. 29, no. 3, pp. 1212–1220, June 2014.

[34] Australian Energy Market Operator (AEMO). Archived pricing event reports. [Online]. Available: https://tinyurl.com/aemoaxv

[35] Australian Energy Regulator (AER). Weekly volume weighted average spot prices. [Online]. Available: https://tinyurl.com/aerstat19

[36] A. Naeem, A. Shabbir, N. Ul Hassan, C. Yuen, A. Ahmad, and W. Tushar, "Understanding customer behavior in multi-tier demand response management program," *IEEE Access*, vol. 3, pp. 2613–2625, 2015.