A Customer-Centric Approach to Bid-Based Transactive Energy System Design

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***Abstract*—This study demonstrates how bid-based transactive energy system designs can be formulated from a customer-centric vantage point to encourage voluntary customer participation. Supportive evidence is provided for distribution systems populated by households with smart electric heating, ventilation and air conditioning systems. The optimal form of a household's bid function is first derived from dynamic programming principles, based solely on the household's general thermal dynamic and welfare attributes. The quantitative form of this optimal bid function is then explicitly derived, given quantitative forms for these attributes. A method is also developed for the systematic construction of household types based on these attributes. Bid comparison, peak load reduction, and target load matching test cases conducted for a 123-bus distribution system illustrate the usefulness of these methods for ensuring bid-based transactive energy system designs are able to align system goals and constraints with local customer goals and constraints.**

***Index Terms*—Transactive energy system design, optimal household bid, household thermal dynamics, household welfare, representative household types, 123-bus test cases.**

I. Introduction

RECENT years have seen a dramatic surge of interest in the restructuring of electric power systems at the distribution level [2]. Researchers and practitioners are exploring new ways to encourage the more active participation of households and businesses in distribution system operations.

Technological innovations include advancements in metering technology. Operational innovations include proposed Transactive Energy System (TES) designs for the support of customer transactions [3], [4]. A *TES design* is a collection of economic and control mechanisms permitting the balancing of power demands and supplies across an entire electrical infrastructure, using value as the key operational parameter [5].

The primary focus of TES design research to date has been the achievement of system efficiency and reliability objectives through appropriate management of customer-owned distributed energy resources.[1] Increasingly, TES design researchers are deriving customer transactions as the outcomes of customer welfare optimization problems, the standard approach in economic theory. However, as discussed more fully in Section II, these optimization problems are typically formulated in a simple generic manner that does not express local customer conditions in an empirically compelling way.

System efficiency and reliability are critically important TES design objectives. However, TES designs must align these system objectives with local customer goals and constraints if voluntary customer participation is to be assured.

Consequently, this study considers the feasibility and desirability of undertaking TES design from a more customer-centric vantage point. For concreteness, attention is focused on bid-based TES designs for distribution systems populated by households. A *bid-based TES design* is a TES design for which valuations are based on purchase and sale reservation values[2] expressed through bids.[3] The main contributions of this study are as follows:

- Dynamic programming principles are used to infer the *optimal* general state-conditioned bid forms for households with smart thermostatically controlled loads whose welfare is measured as comfort minus cost.
- Quantitative forms are derived for these optimal bids, given quantitative forms for the households' thermal dynamic and welfare attributes expressed in terms of base parameters; and a method is developed for clustering households into representative types by means of these base parameters.
- The efficacy of these methods for the formulation and evaluation of bid-based TES designs from a customer-centric vantage point is demonstrated by means of test cases implementing the Five-Step TES Design.

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[1] *Distributed energy resources* include small-scale storage, distributed generation (e.g., solar, wind), and demand response; see [4, p. 6].

[2] A *purchase reservation value* for a quantity q at a time t is the maximum amount a buyer is willing to pay for q at t. A *sale reservation value* for a quantity q at a time t is the minimum amount a seller is willing to accept in payment for the sale of q at t.

[3] In the bid-based TES design literature, a *bid* refers to a demand schedule expressing purchase reservation values for successive quantity units, a supply schedule expressing sale reservation values for successive quantity units, or some combination of the two.

- The *Five-Step TES Design* is a bid-based TES design managed by an Independent Distribution System Operator (IDSO) that supports customer scalability, customer privacy protection, and the alignment of system goals and constraints with local customer goals and constraints.

The households considered in this study are characterized by physical and behavioral attributes. Each household comprises: (i) a house with structural attributes; (ii) a set of appliances that includes an electric Heating, Ventilation, and Air Conditioning (HVAC) system with a smart price-sensitive ON/OFF controller; and (iii) a resident with comfort-cost preferences. Household thermal dynamics are expressed in terms of time-varying temperatures for inside air and inside mass. Household welfare is expressed as resident (thermal) comfort minus the net cost charged for power usage.

The general mathematical form of a household's optimal bid function is characterized in Section III, based solely on dynamic programming principles. Depending on the household's operating state, this optimal bid function expresses either power usage demand as a function of price charged or ancillary service (power absorption) supply as a function of price received.[4]

Quantitative parameterized representations for a household's thermal dynamic system and welfare function are derived in Section IV, expressed in terms of base parameters.[5] A method is then developed in Section V for deriving a household's optimal bid function in quantitative form, expressed in terms of base parameters. In addition, a method is developed in Section VI for classifying households into representative household types, where each type consists of a correlated clustering of base parameter values.

Finally, test cases are reported in Sections VII–VIII to illustrate the usefulness of these methods for the development and evaluation of bid-based TES designs from a customer-centric vantage point. These test cases implement a bid-based IDSO-managed TES design, referred to as the Five-Step TES Design, for a 123-bus distribution system populated by a mix of household types. Outcomes are reported for bid-function comparisons, peak load reduction, and load matching experiments.

Concluding remarks are given in Section IX. Nomenclature tables are provided in an appendix. Test case code and data can be accessed at the repository site [6].

II. Related Literature

TES design research is rapidly expanding. For recent extensive reviews of this research, see Abrishambaf *et al.* [3] and Küster *et al.* [4].

TES design research is most closely associated with the Pacific Northwest National Laboratory (PNNL). As reported in [7], seminal work on transactive designs for power exchange was conducted by PNNL researchers starting as far back as 2003. More recent PNNL TES design work, including field demonstrations, is reported in [8]–[14]. TES design work by other researchers is reported in [15]–[23].

This previous work has developed a wide variety of metrics and simulation tools for the evaluation of TES designs. For example, Widergren *et al.* [13] provide a list of carefully categorized metrics that include convergence rate, frequency of imbalance events, loss of load expectation, and voltage violation counts. Huang *et al.* [14] develop a simulation-based valuation method to compare different transactive energy schemes. They also develop an open-source simulation platform to allow agents developed on different platforms to interact with each other in a flexible manner.

In addition, some of this previous work has focused on the development of new transactive techniques for retail market operations. For example, Rahimi and Ipakchi [15] propose a number of ways in which transactive techniques can be extended from wholesale to retail markets, e.g., how aggregated demand-side resources can be scheduled and dispatched at wholesale in a manner similar to current wholesale resources. Chassin *et al.* [18] propose a transactive policy for the control of loads as demand-response resources able to provide frequency regulating services at wholesale. Mengelkamp *et al.* [21] propose a blockchain-based decentralized microgrid energy market facilitating peer-to-peer energy transactions between retail prosumers and consumers.

More broadly, Renani *et al.* [20] and Nguyen *et al.* [22] propose TES designs for end-to-end power system operations. In these designs, newly proposed forms of distribution system operators function as intermediaries between a system operator at wholesale and aggregated demand-side resources.

With specific regard to bid-based TES design, Hammerstrom *et al.* [8] and Fuller *et al.* [9] propose and implement a linear bid function for retail customers based on average retail price. Kok formulates a simple rectilinear bid function for retail customers with Thermostatically Controlled Loads (TCLs) that can easily be implemented for customers participating in his novel bid-based TES design called the PowerMatcher. Bids are demands for device power usage; ancillary service provision is not considered. The maximum price that retail customers are willing to pay for power usage is modeled as a cut-off price that varies in direct proportion to the difference between actual and desired temperature levels. This bid function form is justified on general heuristic grounds.

Nguyen *et al.* [22] formulate, computationally implement, and evaluate a version of Kok's rectilinear bid function for household-owned electric HVAC systems with smart price-sensitive controllers. The households are participants in a preliminary version of the Five-Step TES Design. Nazir and Hiskens [23] develop a general virtual battery model for TCLs and propose a simple bid function for use as a battery price-sensitive controller.

[4]*Ancillary services* are support services for the maintenance of power balance on a grid in accordance with system reliability requirements. Ancillary service in the form of dispatchable power absorption (withdrawal) is becoming increasingly important for power balance, given the increased penetration of non-dispatchable wind and solar power subject to sudden weather-induced ramping events.

[5]As will be explained more carefully in Section IV, base parameters for a parameterized function are parameters whose specification is both necessary and sufficient for the complete determination of this function. In a software implementation of a parameterized function, the base parameters would constitute the user-set parameters for this function.

The TES design work closest to the current study is by Li *et al.* [12]. The latter authors express a bid-based TES design problem as a mechanism design problem [24] taking the specific form of a Stackelberg game whose participants consist of a Manager (leader) in charge of a collection of TCLs (followers). The Manager uses an energy price signal P_c to coordinate the individual energy allocations selected by the TCLs as a function of P_c and their own private states. The goal of the Manager is to achieve a socially efficient energy allocation subject to customer feasibility conditions and a system peak load constraint.

More precisely, each TCL i selects a temperature setpoint to determine an energy allocation a_i^* that maximizes i's utility, U_i, conditional on the Manager's price signal P_c and i's private state vector θ_i. The utility function U_i is given by i's thermal comfort V_i minus i's energy procurement cost $P_c a_i$. The thermal comfort V_i is assumed to be a concave, strictly increasing, and continuously differentiable function of i's energy allocation a_i over a feasible energy allocation range $[0, E_i^m]$.[6] The state vector θ_i includes i's ON/OFF status and thermal dynamic attributes (internal air and mass temperatures) together with other private information. The optimal energy allocation a_i^* is required to be a continuous non-increasing function of P_c, given θ_i.

The Manager's wholesale energy procurement cost $C(a)$ is assumed to be a differentiable, convex, and increasing function of the sum a of the individual TCL energy allocations a_i. Social welfare is defined to be total TCL utility minus wholesale energy procurement cost.

The *mechanism design problem* is then as follows: Determine bid functions (messages) m_i to be communicated by each TCL i to the Manager that permit the Manager to determine an energy price signal P_c for the TCLs such that the resulting TCL-determined locally optimal energy allocations a_i^* result in the maximization of social welfare subject to TCL feasibility conditions and an overall peak load limit. Li *et al.* [12] establish the existence of bid functions that solve this mechanism design problem, given their assumptions. However, as they note (p. 1176), these bid functions require considerable communication resources. They then simplify their analysis by assuming all TCLs have ON/OFF controllers and TCL bid functions take a piecewise linear form.

In contrast, this study determines optimal state-conditioned bid functions for power customers on the basis of their thermal dynamic and welfare attributes. A customer's optimal bid function can express either a demand for power usage as a function of charged price or a supply of ancillary service as a function of price compensation, depending on the customer's current state. Continually refreshed versions of these optimal bid functions are inputs to a bid-based TES design, referred to as the Five-Step TES Design. The IDSO managing this design sends power price signals to customers to achieve system efficiency and reliability objectives, conditional on these optimal household bid functions.

Another potentially important difference is the switch from the Li *et al.* [12] focus on energy as the transacted product to this study's focus on the production, distribution, and usage of power over time. As discussed at length in [25, Ch. 14], this change in focus from energy to power could facilitate a more coherent comprehensive approach to product settlement.

III. Household Optimal Bid: General Form

Consider a household with an electric HVAC system that is controlled by a smart price-sensitive ON/OFF controller. The goal of the household is to maximize its welfare over time, measured as comfort minus cost. This section uses general dynamic programming principles to derive the optimal general bid-function form for the household's smart HVAC controller.

Let the time-step during which an ON/OFF power setting is maintained for the household's HVAC system be called the *control-step*. Let the time-line for the household be divided into control-steps $n = [n^{\mathsf{s}}, n^{\mathsf{e}})$. At the start-time n^{s} for each control-step n, a control signal is transmitted to the household's HVAC system to either retain or switch its current ON/OFF control setting. This control setting is then maintained for the remainder of control-step n.

The household's goal at the start-time n^{s} for each control-step n is to maximize its welfare over the next N control-steps, where N denotes the household's *look-ahead horizon*. The household at start-time n^{s} then has two possible control-relevant states. Let $\widehat{\mathrm{G}}(n,\mathrm{ON})$ and $\widehat{\mathrm{G}}(n,\mathrm{OFF})$ denote the maximum possible comfort the household forecasts it could achieve over control-steps $n, n+1, \ldots, n+(N-1)$ if its HVAC system at time n^{s} were set to ON or OFF, respectively, and the ON/OFF HVAC controls for the remaining N-1 control-steps $n+1, \ldots, n+(N-1)$ were then optimally set. These two control-relevant states are as follows:

X_n^{s}: *May Run as Ancillary Service Provider*

$$\widehat{\mathrm{G}}(n,\mathrm{ON}) \leq \widehat{\mathrm{G}}(n,\mathrm{OFF})$$

X_n^{u}: *May Run for Power Usage*

$$\widehat{\mathrm{G}}(n,\mathrm{ON}) > \widehat{\mathrm{G}}(n,\mathrm{OFF})$$

If the household is in state X_n^{s} at start-time n^{s}, the household will not be willing to pay a positive price for HVAC power usage during n, no matter how small. However, the household could be induced to switch (or leave) its HVAC system ON if the *price received* for this HVAC power absorption (as ancillary service supply) is *sufficiently high*. Let this sufficiently high cut-off price be denoted by $-\Pi^*(X_n^{\mathsf{s}}) \geq 0$.

Conversely, if the household is in state X_n^{u} at start-time n^{s}, the household will be willing to pay a positive price for HVAC power usage during n as long as this *price charged* is *sufficiently low*. Let this sufficiently low positive cut-off price be denoted by $\Pi^*(X_n^{\mathsf{u}}) > 0$.

Consequently, the household's optimal bid function for control-step n has the general rectilinear form depicted in Fig. 1, where $P^*(n)$ denotes the ON power consumption of the household's HVAC system during control-step n.

Note the optimal bid form in the ancillary service state X_n^{s} constitutes a *supply* function for ancillary service (HVAC

[6]Note that these restrictions on V_i rule out the existence of an *interior* "bliss point" a^{bliss} for the energy allocation a_i at which i's comfort attains its maximum value. As will be seen in Section V, below, the existence of such a bliss point would give i an opportunity to offer ancillary service (power absorption) in return for appropriate compensation.

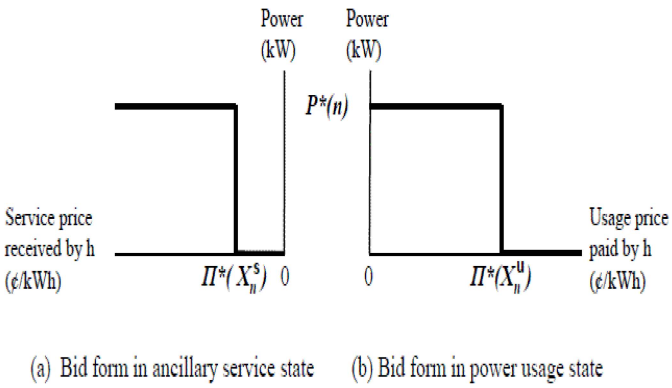

Fig. 1. A household's optimal state-dependent "May Run" bid forms for (a) ancillary service provision and (b) power usage during a control-step n. A negative price denotes a price received by the household for provision of ancillary service (HVAC power absorption). A positive price denotes a price paid by the household for HVAC power usage.

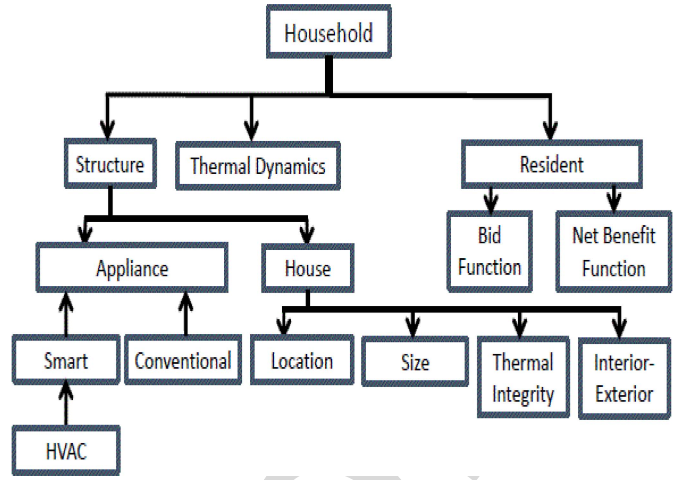

Fig. 2. Classification of household physical and behavioral attributes.

power absorption) as a function of price *received*. Conversely, the optimal bid form in the power usage state X_n^{u} constitutes a *demand* function for HVAC power usage as a function of price *paid*.

IV. Quantitative Derivation of Household Optimal Bid Functions: Preliminaries

A. Household Formulation: Overview

Consider a household that consists of a resident occupying a house at a particular location subject to external hot weather conditions. The household has a mix of smart (price-responsive) and conventional appliances.

Specifically, the household has a smart electric HVAC system *running in cooling mode* with ON/OFF power settings. This HVAC system comprises a basic HVAC unit operating in parallel with a one-speed fan for air circulation. The household's conventional appliances consist of lights, clothes-washer, refrigerator, dryer, freezer, range, and microwave.[7]

The household participates in a bid-based TES design managed by an IDSO. The household sends bids to the IDSO that express its demands for HVAC power usage as a function of required price payment and its supplies of ancillary service (HVAC power absorption) as a function of offered price compensation. In return, the IDSO sends price signals to the household that determine ON/OFF power control actions for the household's smart HVAC system.

Fig. 2 classifies the household's physical and behavioral attributes into conceptually distinct categories. Downward-pointing arrows denote "has a" relationships and upward-pointing arrows denote "is-a" relationships.

The 'Structure' of the household is characterized by appliance and house attributes. Appliance attributes include appliance mix and appliance features. House attributes include location, size, thermal properties, and interior-exterior features such as window framing and glazing.

The 'Resident' of the household is characterized by bid and net benefit functions. The 'Bid Function' expresses the resident's demand for HVAC power usage or supply of ancillary service (HVAC power absorption), conditional on price signals and current operating conditions. The 'Net Benefit Function' expresses resident welfare as benefit net of cost. Benefit is measured by thermal comfort. Cost is measured by charges for power usage net of payments for ancillary service.

The household's thermal dynamics are expressed as a dynamic system with two state variables: internal air temperature, and internal mass temperature. Starting from initial conditions, the motion over time of these two state variables is determined by external forcing terms and by HVAC ON/OFF power control actions. This thermal dynamic modeling is carefully based on the household's 'Structure' and 'Resident' attributes.

B. Household Methods: Discretization

In the following two subsections, a household's thermal dynamic system and net benefit function are represented in specific quantitative discretized forms.[8]

For this purpose, the time-line $[t_0, +\infty)$ is partitioned into *control-steps* n of equal length $\Delta\tau$ (seconds), where $1/\Delta\tau$ is the rate at which the household's HVAC system receives ON/OFF power control signals. Each control-step $n = 0, 1, \ldots$ takes the form $n = [n^{\mathrm{s}}, n^{\mathrm{e}})$, where the *start-time* n^{s} and *end-time* n^{e} are defined as $n^{\mathrm{s}} = t_0 + n\Delta\tau$ and $n^{\mathrm{e}} = t_0 + [n+1]\Delta\tau$.

A function $f : [t_0, +\infty) \to R$ can then be expressed in a discretized form $f^*(n)$ that comports with this partitioning, as follows: For each control-step n, $f^*(n) \equiv f(n^{\mathrm{s}})$.

C. Household Thermal Dynamics: Specific Form

Household thermal dynamics are expressed by an Equivalent Thermal Parameter (ETP) model [26], [27]

[7] The methods developed in this study for optimal bid formulation and type classification can be applied for households with HVAC systems running in heating as well as cooling mode, and with arbitrary mixes of conventional appliances. Specific appliance assumptions are made here to enable a concrete demonstration of these methods.

[8] Careful derivations of these discretized forms from continuous-time representations are given in [1, Secs. 5-6].

describing the movement of two state variables, internal air temperature $T_a^*(n)$ and internal mass temperature $T_m^*(n)$, over discrete control-steps $n = 0, 1, \ldots$ External forcing terms for each control-step n include the outside air temperature $T_o^*(n)$. The control variable $u^*(n)$ for each control-step n is the ON/OFF HVAC setting determined by the household's HVAC controller.

The specific quantitative form of this thermal dynamic system is as follows. For each control-step $n = 0, 1, \ldots$

$$x^*(n+1) = x^*(n) + A[K_h\Delta\tau]x^*(n) + B[K_h\Delta\tau]v^*(n) \quad (1)$$

where:

$$A = \begin{bmatrix} -\frac{U_a+H_m}{C_a} & \frac{H_m}{C_a} \\ \frac{H_m}{C_m} & -\frac{H_m}{C_m} \end{bmatrix};$$

$$B = \begin{bmatrix} \frac{U_a}{C_a} & \frac{1}{C_a} & 0 \\ 0 & 0 & \frac{1}{C_m} \end{bmatrix};$$

$$x^*(n) = \begin{bmatrix} T_a^*(n) \\ T_m^*(n) \end{bmatrix};$$

$$v^*(n) = \begin{bmatrix} T_o^*(n) \\ Q_a^*(n) \\ Q_m^*(n) \end{bmatrix};$$

$$\begin{aligned} Q_a^*(n) &= \left[1-f_i\right]Q_i^*(n) + \left[1-f_s\right]Q_s^*(n) \\ &\quad + \left[1-f_{\mathsf{ac}}\right]Q_{\mathsf{hvac}}^*(n); \\ Q_m^*(n) &= f_iQ_i^*(n) + f_sQ_s^*(n) + f_{\mathsf{ac}}Q_{\mathsf{hvac}}^*(n); \\ Q_{\mathsf{hvac}}^*(n) &= \left(-K^*(n)P_{\mathsf{hvac}}^*(n) + KP_{\mathsf{fan}}\right)u^*(n); \\ P^*(n) &= P_{\mathsf{hvac}}^*(n) + P_{\mathsf{fan}}. \end{aligned} \quad (2)$$

Straightforward but lengthy additional equations expressing the heat flow rates $Q_i^*(n)$ and $Q_{\mathsf{s}}^*(n)$, the conversion factor $K^*(n)$, the ON power usage $P_{\mathsf{hvac}}^*(n)$ of the main HVAC unit, and the ON power usage P_{fan} of the HVAC air circulation fan as functions of household parameters and external forcing terms can be found in Tesfatsion and Battula [27, Sec. 4.3]. These additional equations are omitted from the current study due to page-length limitations.

Fuller descriptions for all terms appearing in the thermal dynamic system (1) are given in nomenclature tables provided in an appendix to this study.

D. Household Net Benefit: Specific Form

The *net benefit* of a household during any time interval is defined to be the (thermal) comfort attained by the household minus its net cost for power withdrawal from the distribution grid. This section derives an explicit quantitative expression for the forecasted net benefit of a household for a control-step n, measured at the start-time n^{s} for n. Recall that $\Delta\tau$ denotes the length (in seconds) of each control-step n.

The comfort attained by a household during any control-step n is measured as the deviation between the household's maximum attainable comfort ($G_{\mathsf{max}}\Delta\tau$) and the household's discomfort. As in [16], [28], the household's discomfort is measured by the discrepancy between inside air temperature and the *bliss temperature* TB at which the household attains maximum comfort.

The *forecasted comfort* of a household for control-step n, calculated at the start-time n^{s} for n, is given by

$$\widehat{\mathrm{G}}^*(n) = \left[G_{\mathsf{max}} - \widehat{H}^*(n)\right]\Delta\tau \quad (3)$$

where the *forecasted discomfort* $\widehat{H}^*(n)$ is given by

$$\widehat{H}^*(n) = \left(h_1\left[T_a^*(n) - \mathrm{TB}\right]^2 + h_2\left[E_n\left[T_a^*(n+1)\right] - \mathrm{TB}\right]^2\right) \quad (4)$$

with positive weights h_1 and h_2. The term $E_n[T_a^*(n+1)]$ in (4) denotes the household's forecast[9] for the future inside air temperature $T_a^*(n+1)$ at the start-time for control-step n+1, conditional on the household's current state at n^{s} and the ON/OFF HVAC control action to be taken at n^{s}.

The *forecasted net cost* of a household for control-step n, calculated at the start-time n^{s} for n, is given by

$$\widehat{\mathrm{C}}^*(n) = \left[K_h\pi^*(n)\right]P^*(n)\Delta\tau \cdot u^*(n). \quad (5)$$

The term $K_h\pi^*(n)$ (¢/kW·s) in (5) denotes the retail power price $\pi^*(n)$ (¢/kWh) converted by K_h to ¢/kW·s. As will be clarified below in Section V, the retail power price $\pi^*(n)$ can be either positive or negative in sign. A *positive* retail power price denotes a price *charged* for demanded power usage, and a *negative* retail power price denotes a price *received* for supplied ancillary service (power absorption).

As seen in (2), the expression $P^*(n)$ (kW) in (5) denotes the total power consumption of the household's HVAC system at the start-time n^{s} if the system is ON. The control variable $u^*(n)$ equals 1 (or 0) if the household's HVAC system is set to ON (or OFF) at the start-time n^{s}.

Finally, the *forecasted net benefit* of a household for control-step n, calculated at the start-time n^{s} for n, is given by

$$\widehat{\mathrm{NB}}^*(n) = \widehat{\mathrm{G}}^*(n) - \mu\widehat{\mathrm{C}}^*(n). \quad (6)$$

The factor $\mu > 0$ in (6) denotes the household's *marginal utility of money* (utils/¢), a standard economic concept used to transform prices measured as money per quantity unit into prices measured as benefit (utility) per quantity unit.[10]

E. Household Parameter and Forcing Term Settings

This subsection suggests possible ways that numerical values could be set for the parameters and forcing terms characterizing the thermal dynamic and welfare attributes of our modeled household, thus permitting practical implementation.

Regarding the household thermal dynamic system (1), values for the four main thermal parameters $\{C_a, C_m, U_a, H_m\}$ and the three weight factors $\{f^i, f_s, f_{ac}\}$ can be determined from the physical attributes of a house, such as the floor area, the number of stories, the orientation and size of windows and doors, and the level of thermal insulation. Relationships expressing C_a, C_m, U_a, and H_m as functions of physical house attributes are carefully presented and explained in [27, Sec. 4.4]. Values for HVAC system parameters, such as the HVAC system's

[9]The precise manner in which this forecast is calculated is carefully explained in [1, App. B].

[10]See [1, Sec. 5.1] for a fuller discussion of the meaning and derivation of a household's marginal utility of money.

cooling-mode coefficient of performance that enters into the determination of the ON power usage $P^*(n)$ for the HVAC system running in cooling mode, can be obtained from the HVAC system installer or manufacturer.

Relationships expressing the heat flow rates $Q_s^*(n)$ and $Q_i^*(n)$ as functions of forcing terms and physical house attributes are carefully presented and explained in [27, Sec. 4.2]. The heat flow rate $Q_s^*(n)$ from solar radiation to inside air mass and inside solid mass can be calculated from incident solar radiation and physical house attributes. However, obtaining an accurate estimate for the heat flow rate $Q_i^*(n)$ from internal non-HVAC equipment usage and house occupancy to inside air mass and inside solid mass presents quite a practical challenge since these determining factors depend on resident behavior. Some form of typical variation for $Q_i^*(n)$ would presumably have to be used based on information provided by the resident and/or by sites such as [28].

Another issue is the determination of the internal mass temperature $T_m^*(n)$, appearing as the second component of the state vector $x^*(n)$ for the thermal dynamic system (1). This internal mass temperature cannot be obtained by direct measurement. However, as demonstrated in [16, App. A], a Luenberger observer can be designed to estimate this state variable using environmental variable measurements for outside air temperature, solar radiation, and humidity together with reasonable assumptions regarding heat flow rates. Environmental variable measurements can be obtained either directly, by sensors installed at the house, or indirectly from weather monitoring websites.

The representation (6) for a household resident's forecasted net benefit (comfort minus cost) is roughly based on [28]. The resident could program his comfort and cost preferences either directly on a wall control unit or by means of a user-friendly graphical user interface that runs on some form of mobile computing device. The wall unit or mobile computing device could permit the resident to enter his preferences in a user-friendly (non-numerical) manner that is internally translated into numerical values.

For example, to determine the bliss temperature TB, the resident could be asked to set a slider control between minimum and maximum temperature limits. Given an arbitrary positive pre-set value for G_{max} in (3), the weight factors h_1 and h_2 appearing in expression (4) for forecasted discomfort could reasonably be set to equal scaled values $K_d/2$. Forecasted discomfort for a control-step n would then be approximated as the scaled average deviation between TB and the actual (or forecasted) inside air temperature at the start-time and end-time for n. To determine the scale factor K_d, the resident could be asked to set a slider control between 0 and G_{max}. Finally, to determine the comfort-cost trade-off parameter μ, the resident could be asked to set a slider control between minimum and maximum limits corresponding to "cost is not important (relative to comfort)" and "cost is highly important (relative to comfort)".

V. Optimal Household Bid Function Derivation

Consider a household whose thermal dynamic system and forecasted net benefit function take the parameterized forms presented in Sections IV-C and IV-D. The *base parameter set* $\mathbb{BP}$ for this household is defined by the following three conditions: (i) Each element of $\mathbb{BP}$ is a parameter appearing in the household's thermal dynamic system or forecasted net benefit function; (ii) Each parameter appearing in the household's thermal dynamic system and forecasted net benefit function can be expressed as a function of one or more parameters in $\mathbb{BP}$; (iii) No parameter in $\mathbb{BP}$ can be non-trivially expressed as a function of other parameters in $\mathbb{BP}$.

Thus, in standard mathematical terms, $\mathbb{BP}$ constitutes a *basis set* for the parameters appearing in the household's thermal dynamic system and forecasted net benefit function. Let β denote the household's *base parameter vector* consisting of all of the elements of $\mathbb{BP}$. A complete listing of all of the components of β, together with their descriptions and units of measurement, is given in [1, Tab. 12].

Dynamic programming principles were used in Section III to obtain the general state-dependent form of a household's optimal bid function for a control-step n, given an arbitrary look-ahead horizon $N \geq 1$; see Fig. 1. Treatment of multi-period look-ahead horizons $N > 1$ is conceptually straightforward but computationally more demanding than treatments of single-period look-ahead horizons N=1 due to the infamous dynamic programming "curse of dimensionality."[11] Consequently, for simplicity of exposition, this section derives a specific quantitative expression for the household's optimal state-dependent bid function in terms of the household's base parameter vector β under the presumption that N=1.

The power level $P^*(n, \beta)$ corresponding to $P^*(n)$ in Fig. 1 denotes the ON power consumption of the household's HVAC system running in cooling mode during n, as determined by (2). Suppose the household's HVAC system is switched (or left) OFF at the start-time n^{S} for control-step n. Let the household's resulting forecasted net benefit (6) be denoted by:

$$\widehat{\mathrm{NB}}^*(n, \beta, \mathrm{OFF}) = \widehat{\mathrm{G}}^*(n, \beta, \mathrm{OFF}). \tag{7}$$

Conversely, suppose the household's HVAC system is switched (or left) ON at n^{S}. Let the household's resulting forecasted net benefit (6) be denoted by:

$$\begin{aligned}\widehat{\mathrm{NB}}^*(n, \beta, \mathrm{ON}) &= \widehat{\mathrm{G}}^*(n, \beta, \mathrm{ON}) - \mu \mathrm{C}^*(n, \beta, \mathrm{ON}) \\ &= \widehat{\mathrm{G}}^*(n, \beta, \mathrm{ON}) - \mu K_h \pi^*(n) P^*(n, \beta) \Delta\tau \end{aligned} \tag{8}$$

Since the goal of the household is to maximize its forecasted net benefit during n, the household will be willing to switch

[11]Consider a dynamic programming problem spanning N future periods $0, 1, \ldots, N-1$ with $N \geq 1$. The solution of this problem starts with the assignment of a value to each possible system outcome that could occur during the final period N-1 as a result of each possible decision at the start of period N-1 in each possible state that the system could be in at the start of period N-1. The *curse-of-dimensionality* refers to the fact that the number of possible system states at the start of period $N-1$ increases exponentially with increases in N if the decision set of the decision-maker at the beginning of each period includes at least two distinct decision choices. For example, for the problem at hand, the HVAC controller can set the HVAC system to either ON or OFF at the beginning of each control-step $n = 0, 1, \ldots$ Assuming each possible setting results in a different next-period starting state (or state set), there are (at least) 2^{N-1} possible starting states for period N-1 corresponding to any particular starting state at the start of period 0. The possible gain in value from using a longer look-ahead horizon N must therefore be weighed against increased computational cost.

(or leave) its HVAC system ON during n if and only if

$$\widehat{\mathrm{NB}}^*(n, \beta, \mathrm{OFF}) \leq \widehat{\mathrm{NB}}^*(n, \beta, \mathrm{ON}). \quad (9)$$

Substituting (7) and (8) into (9), and rearranging terms, condition (9) is equivalent to

$$\pi^*(n) \leq \frac{\left[\widehat{\mathrm{G}}^*(n, \beta, \mathrm{ON}) - \widehat{\mathrm{G}}^*(n, \beta, \mathrm{OFF})\right]}{\mu K_h P^*(n, \beta)\Delta\tau} \equiv F_n(\beta). \quad (10)$$

The power usage state $X_n^{\mathsf{u}}(\beta)$ corresponding to X_n^{u} in Fig. 1 is the β-dependent household state in which the household is willing to *pay* for *power usage* during control-step n. It follows from the derivation of relation (10) that the household is in a power usage state $X_n^{\mathsf{u}}(\beta)$ at the start of control-step n if and only if $F_n(\beta)$ in (10) is strictly positive in value. In this case there is a range of positive prices $\pi^*(n)$ for power usage during control-step n that the household is willing to pay, bounded above by the positive cut-off price $\Pi^*(X_n^{\mathsf{u}}(\beta))$ given by $F_n(\beta)$.

Consequently, the household's optimal bid function in a power usage state $X_n^{\mathsf{u}}(\beta)$ takes the rectilinear form depicted on the right-hand side of Fig. 1. This optimal bid function constitutes a *demand function* for HVAC power usage as a function of price *paid*.

Conversely, the ancillary service state $X_n^{\mathsf{s}}(\beta)$ corresponding to X_n^{s} in Fig. 1 is the β-dependent household state in which the household *is not* willing to pay for power usage during control-step n but is willing to provide ancillary service (HVAC power absorption) during n in return for sufficiently high compensation. It follows from the derivation of relation (10) that the household is in an ancillary service state $X_n^{\mathsf{s}}(\beta)$ at the start of control-step n if and only if $F_n(\beta)$ in (10) is less than or equal to zero. In this case the household can be induced to switch (or leave) its HVAC system ON during n if and only if the *price received* for ancillary service, $-\pi^*(n)$, is at least as high as the non-negative cut-off price $-\Pi^*(X_n^{\mathsf{s}}(\beta))$ given by $-F_n(\beta)$.

Consequently, the form of the household's optimal bid function in an ancillary service state $X_n^{\mathsf{s}}(\beta)$ takes the rectilinear form depicted on the left-hand side of Fig. 1. This optimal bid function constitutes a *supply function* for ancillary service as a function of price *received*.

Complete explicit derivations of a household's optimal bid cut-off prices $\Pi^*(X_n^{\mathsf{u}}(\beta))$ and $-\Pi^*(X_n^{\mathsf{s}}(\beta))$ as functions of its base parameter vector β are provided in [1, App. C].

VI. Household Type Classification

This section develops a method for classifying households into representative types in accordance with the values set for the components of each household's base parameter vector β.

As shown in Fig. 2, the 'Structure' attributes of a household are divided into 'Appliance' and 'House' attributes. Let β^a denote the components of β that correspond to 'Appliance' attributes, and let β^h denote the components of β that correspond to 'House' attributes. Finally, let β^r denote the components of β that correspond to 'Resident' attributes. A *Household Type* is then defined by three aspects: *Appliance Type* (β^a), *House Type* (β^h), and *Resident Type* (β^r). A complete description of the components of $\beta = (\beta^a, \beta^h, \beta^r)$, classified by attribute type, is given in [1, Tab. 12].

To be physically and economically meaningful, the base parameters comprising β for any given household must be configured in a correlated manner. For example, it would be empirically problematic to assume that a household with a small-sized house, located in a temperate climate, has a large powerful HVAC system.

For concreteness, suppose a household's *Structure Quality Type (SQT)* is characterized by its *HVAC Type* (β^{hvac}) and its House Type (β^h), where β^{hvac} consists of all base parameters in the household's Appliance Type β^a that correspond to the attributes of its HVAC system. As seen in [1, Tab. 12], β^{hvac} thus includes an HVAC system's coefficient of performance (cooling_COP) and over-sizing factor (OSF); and a household's House Type β^h characterizes the location, size, thermal integrity, and interior-exterior attributes of its house.

Different SQTs can then be constructed using different correlated settings for the base parameters in β^{hvac} and β^h, with all remaining elements of β maintained at fixed value settings. For example, in the test cases reported below in Sections VII–VIII, a household has a *Low* SQT if it has a 'Small' sized house, 'Poor' thermal integrity, 'Poor' interior-exterior features, and a 'Poor' quality HVAC system. It has a *Medium* SQT if it has a 'Normal' sized house, 'Normal' thermal integrity, 'Normal' interior-exterior features, and a 'Normal' HVAC system. It has a *High* SQT if it has a 'Large' sized house, 'Good' thermal integrity, 'Good' interior-exterior features, and a 'Good' quality HVAC system.[12]

VII. Test Case Preliminaries

A. Grid and Household Formulation

The standard IEEE 123-bus distribution grid [29] is modified for our test cases in three ways. First, 927 households are distributed across the 123 buses in proportion to the original loads, which are then omitted. Second, the distribution grid is connected to a transmission grid through a substation; wholesale power is supplied to the distribution system through this T-D interface. Third, the distribution system is managed by an IDSO operating at this substation; see Fig. 3.

Each household is formulated using our household model and implemented in part using the GridLAB-D (GLD) House Object [30].[13] Weather forcing terms consist of outside temperature, solar flux, and humidity data for hot summer days in Des Moines, Iowa. The base parameter location attributes specified for each household are also for Des Moines, Iowa. The base parameter welfare attributes maintained for each household are: G_{max} = 3.3333 (utils/s); TB = 72 (°F); and $h_1 = h_2 = .0017$ (utils/[s - (°F)^2]). The base parameters NOC and f_{oc} appearing in each household's Resident Type β^r are set to 1 and 1.0, respectively. The setting NOC = 1 indicates the household has a single resident, and the setting $f_{\mathsf{oc}} = 1.0$ indicates this resident occupies the house 100% of the time.

[12] The specific correlated parameter settings used to characterize Low, Medium, and High SQTs are given in [1, App. F].

[13] See [1, App. E] for GLD House Object implementation details.

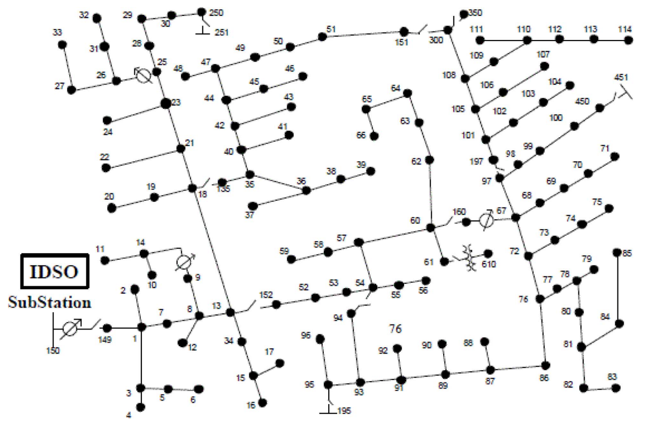

Fig. 3. IEEE 123-bus distribution grid modified to include an IDSO operating as a T-D linkage entity at a substation connected to a transmission grid.

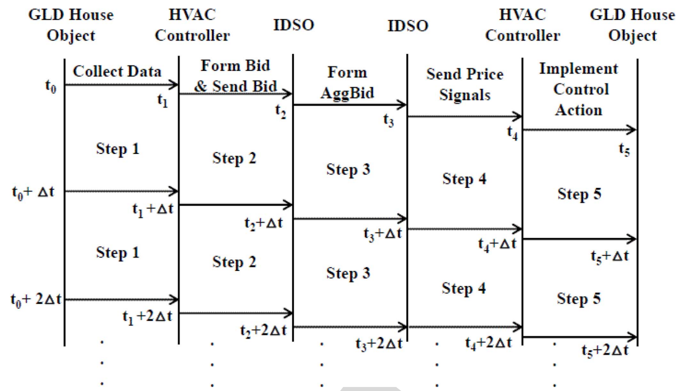

Fig. 4. Staggered-step implementation of the Five-Step TES Design.

B. Five-Step TES Design

All test-case households participate in an IDSO-managed bid-based TES design for the management of their power consumption. This design, referred to as the *Five-Step TES Design*, consists of the iterated implementation of five steps characterized by five action time-rates, as follows[14]:

- *Step 1:* The HVAC controller for each household h collects data on the state of h at a *data check rate*.
- *Step 2:* The HVAC controller for each household h forms a state-conditioned bid function Bid(h) for HVAC power usage demand or ancillary service supply and communicates it to the IDSO at a *bid refresh rate*.
- *Step 3:* The IDSO combines the household bid functions Bid(h) into a vector AggBid of aggregate bid functions at an *aggregate bid refresh rate*.
- *Step 4:* The IDSO uses AggBid to determine and communicate price signals back to household HVAC controllers at a *price signal rate.*
- *Step 5:* The HVAC controller for each household h inserts its latest received price signal into its latest refreshed state-conditioned bid function Bid(h) at a *power control rate*, which triggers an ON/OFF power control action for the HVAC system.[15]

Customer scalability, customer privacy, and the alignment of system goals and constraints with local customer goals and constraints are important design criteria motivating our formulation and use of the Five-Step TES Design.

Scalability is facilitated by employing a radial two-way communication network between the IDSO and participant households. In practice, real-time telemetry supporting two-way communication would be needed to implement this design. However, U.S. energy regions interested in smart grid development are already moving ahead with plans to implement two-way real-time telemetry.[16]

[14]The Five-Step TES Design is a variant of the PowerMatcher TES design developed by Koen Kok [17].

[15]The power control rate is given by $1/\Delta\tau$, where $\Delta\tau$ is the length in seconds of each control-step n; see Section IV-B.

[16]For example, ERCOT [33] has installed two-way real-time telemetry to support the ability of "Qualified Scheduling Entities" to submit price-sensitive demand bids into its day-ahead and real-time markets on behalf of load-serving entities functioning as demand-response resources.

Privacy is protected by permitting household bids in Step 2 to take the optimal state-conditioned form depicted in Fig. 1 for each control-step n. Specifically, Bid(h) for a household h in an *ancillary service* state $X^{\mathsf{s}}_{h,n}$ consists of a *negatively*-valued cut-off price $\Pi^*(X^{\mathsf{s}}_{h,n})$ together with a forecast $P^*_h(n)$ for the ON power usage of h's HVAC system. Similarly, Bid(h) for a household h in a *power usage* state $X^{\mathsf{u}}_{h,n}$ consists of a *positively*-valued cut-off price $\Pi^*(X^{\mathsf{u}}_{h,n})$ together with a forecast $P^*_h(n)$ for the ON power usage of h's HVAC system. Consequently, the amount of private information that households must convey to the IDSO in Step 2 of the Five-Step TES Design is minimal.

Finally, the alignment of system goals and constraints with private goals and constraints is facilitated by Step 4 of the design. As will be illustrated in Section VIII, the system efficiency and reliability goals pursued by an IDSO can take a wide variety of forms. However, whatever form these system goals take, Step 4 ensures they are implemented in accordance with local household goals and constraints as expressed by means of continually refreshed household bid functions.

For simplicity, the five action time-rates for the Five-Step TES Design are commonly set equal to $1/\Delta t$ with time-step $\Delta t = 300$s for each test case reported in Section VIII. Let the time-delay between Step j and Step $j+1$ in any given iteration of the five steps be denoted by ϵ_j for $j = 1, \ldots, 5$, where "Step 6" is equated with "Step 1" in the subsequent iteration. The time delays ϵ_j for each test case are commonly set so that their summation does not exceed Δt. Finally, let $t_j = t_{j-1} + \epsilon_j$ for $j = 1, \ldots 5$. Then, for each reported test case, the iterated staggered implementation of the five steps comprising the Five-Step TES Design is as depicted in Fig. 4.

However, the specification of the five action time-rates for the Five-Step TES Design is in fact a critical design choice with important performance and cost ramifications at both household and system levels.

At the household level, Ilić *et al.* [31, Sec. 3] document how longer cycle periods (slower power control rates) can degrade the coefficient of performance for residential air-conditioning systems due to efficiency losses arising from various operational side-effects. On the other hand, shorter cycle periods (faster power control rates) can result in costly wear-and-tear and shorter lifetimes for system components. Indeed, as stressed by Wu *et al.* [32], HVAC manufacturers commonly install minimum ON/OFF time constraints in HVAC equipment to prevent these types of equipment degradation problems.

At the system level, the joint specification of the five action time-rates could affect the ability of the IDSO in Step 4 to maintain efficient and reliable system operations. For example, it is not efficient to have a data check rate or a bid refresh rate that exceeds the power control rate; the faster local time-rates would require additional local computations, yet they would not have any effect on actual power usage.

C. Hardware Implementation

Each of the test cases reported below in Section VIII was run on a machine with a 3.5 GHz 4-Core Intel Xeon CPU E3-1240 v5 processor, a Windows 10 Enterprise operating system, and 16 GB of RAM.

VIII. Test Case Outcomes

A. Purpose

Household test case outcomes are reported in this section to demonstrate the usefulness of our optimal bid formulation and representative type construction method for the customer-centric development and evaluation of bid-based TES designs. Three different types of test cases are considered: bid-function comparisons; peak-load reduction experiments; and target load matching experiments. A key treatment factor for each of these test cases is household structure quality as measured by the SQT metric defined in Section VI.

B. Test Case 1: Bid Function Performance Comparisons

This subsection reports the increase in household net benefit (comfort minus cost) that results for a control-step n when a household switches from the use of the heuristically motivated bid function developed by Nguyen *et al.* [22] to the optimal bid function derived in Section V of this study with look-ahead horizon N=1.

The heuristic bid function developed by Nguyen *et al.* [22] for a household resident R specifies cut-off prices for ancillary service provision and power usage that vary in direct proportion to the deviation between R's bliss temperature TB and the current inside air temperature $T_a^*(n)$ of R's house, as follows:

$$\Pi^{\mathsf{s}}\big(T_a^*(n)\big) = \theta^{\mathsf{s}}\left[\frac{T_a^*(n) - \mathrm{TB}}{\mathrm{TB} - \mathrm{T}^{\mathsf{min}}}\right],\ \mathrm{T}^{\mathsf{min}} < T_a^*(n) \le \mathrm{TB}; \tag{11}$$

$$\Pi^{\mathsf{u}}\big(T_a^*(n)\big) = \theta^{\mathsf{u}}\left[\frac{T_a^*(n) - \mathrm{TB}}{\mathrm{T}^{\mathsf{max}} - \mathrm{TB}}\right],\ \mathrm{TB} < T_a^*(n) < \mathrm{T}^{\mathsf{max}}, \tag{12}$$

where θ^{s} and θ^{u} are positively-valued scaling parameters. The test case parameter values maintained for this heuristic bid formulation are: $\mathrm{T}^{\mathsf{min}} = 68°F$, $\mathrm{TB} = 72°F$, $\mathrm{T}^{\mathsf{max}} = 76°F$, and $\theta^{\mathsf{s}} = \theta^{\mathsf{u}} = 20$ (¢/kWh).

The net benefit that results during a control-step n from the use of the heuristic bid function (11) and (12) is compared with the net benefit that results from the use of the optimal bid function under variously set values for the household's marginal utility of money μ and the household's structure quality as measured by SQT. The initial inside air temperature and initial outside weather temperature for control-step n are set at $T_a^*(n) = 74.67$ (°F) and $T_o^*(n) = 79$ (°F), respectively, for both bid formulations.

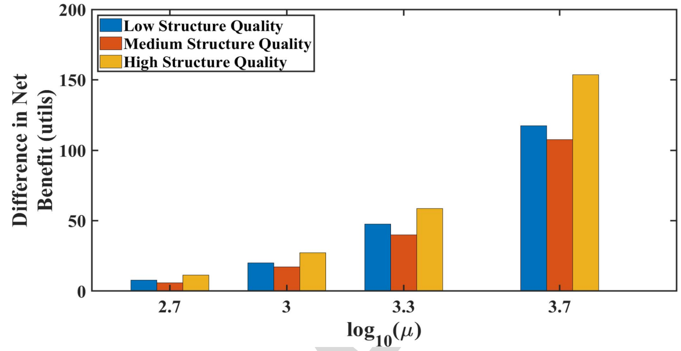

Fig. 5. Increase in net benefit resulting when a household switches from the heuristic bid function developed in [22] to our optimal bid function, under varied settings for household marginal utility of money μ^{m} (utils/\$) and structure quality.

The outcomes reported in Fig. 5 for this test case show that the optimal bid function results in higher net benefit for all tested values for μ^{m} (utils/\$), where $\mu^{\mathsf{m}} = \mu \times 100¢/1\$$. This net benefit improvement is larger for larger μ^{m} values. Moreover, this same pattern holds across all three tested settings for household structure quality.

As seen in Section III, the general form of our optimal bid function, depicted in Fig. 1, is correct for an arbitrary look-ahead horizon $N \ge 1$. The increased foresight provided by implementing a longer look-ahead horizon $N > 1$ is another potential source of net benefit improvement from the use of our optimal bid function in place of the heuristic bid function (11) and (12). However, as discussed in Section V, this potential improvement must be weighed against increased computational cost. In addition, since our optimal bid function depends on forecasted future values for inside air temperature, another potential drawback to the use of a longer look-ahead horizon is increased forecast error.

C. Test Case 2: IDSO Peak Load Reduction Capabilities

This subsection reports outcomes for test cases in which the system goal of an IDSO managing a Five-Step TES Design for households on day D is to achieve a reduction target for household peak load on day D+1.

The IDSO on day D forecasts a 24-hour profile for total household load on day D+1, assuming a flat retail price $\overline{\pi}$ = 12¢/kWh[17] for all hours of day D+1. The IDSO uses this forecasted load profile to estimate a *peak load* PL (MW) for day D+1 together with a *target peak load reduction* TPLR (MW) for day D+1 satisfying $0 \le \mathrm{TPLR} < \mathrm{PL}$. The IDSO on day D+1 then uses its continually refreshed vector AggBid of household aggregate bid functions to calculate and send retail price signals to households that ensure realized total household load never exceeds $\mathrm{L}^{\mathsf{max}}$ = [PL-TPLR] during day D+1.

[17] The flat retail price 12¢/kWh is based on average retail electricity rates for Des Moines, Iowa. As noted in Section VII-A, weather data and household location attributes for this test case are also for Des Moines, Iowa.

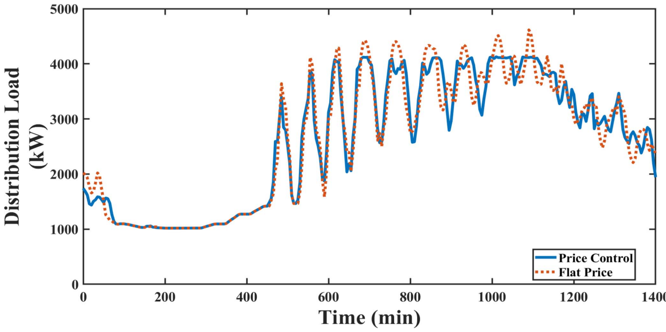

Fig. 6. Low SQT Case: Load outcomes on day D+1 when the IDSO controls retail prices to achieve a 0.5MW target peak load reduction with all Low SQT households.

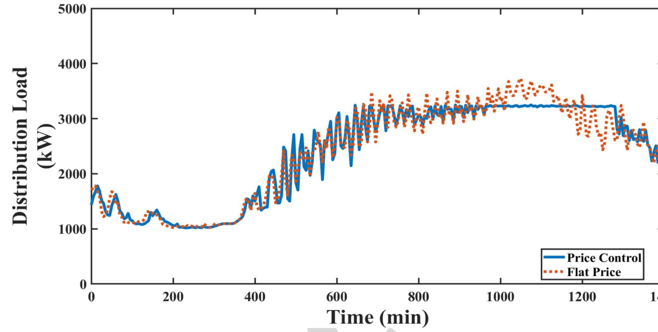

Fig. 7. Medium SQT Case: Load outcomes on day D+1 when the IDSO controls retail prices to achieve a 0.5MW target peak load reduction with all Medium SQT households.

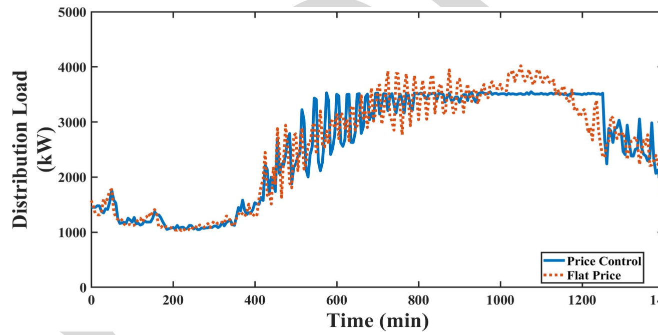

Fig. 8. High SQT Case: Load outcomes on day D+1 when the IDSO controls retail prices to achieve a 0.5MW target peak load reduction with all High SQT households.

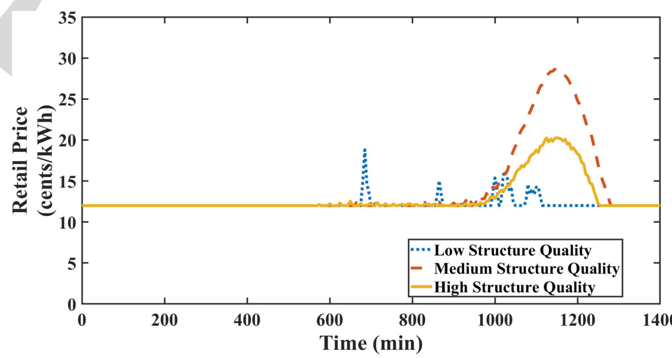

Fig. 9. IDSO-controlled retail price signals used by the IDSO on day D+1 to achieve a 0.5MW target peak load reduction under three different household SQT treatments: all Low; all Medium; or all High.

More precisely, at the start-time for any price-step[18] k on day D+1, AggBid consists of two distinct aggregate bid functions: one constructed from the optimal bid functions submitted by households in a power usage state (identified by their submission of positive cut-off prices); and a second one constructed from the optimal bid functions submitted by households in an ancillary service state (identified by their submission of negative cut-off prices). Since ancillary service (power absorption) is not useful for achieving peak load reduction, the IDSO sends a price signal 0 to all households in an ancillary service state. If the forecasted load for k given $\overline{\pi}$ does *not* exceed L^{max}, the IDSO sends the price signal $\overline{\pi}$ to all households in a power usage state. If the forecasted load for k given $\overline{\pi}$ *does* exceed L^{max}, the IDSO sends a price signal $\pi > \overline{\pi}$ to all households in a power usage state that lowers aggregate power usage demand down to L^{max}.

The treatment factor for this test case is household structure quality, as measured by the metric SQT explained in Section VI.[19] Each household's marginal utility of money μ is set to 1 (utils/¢). All other household attributes are set at the maintained values given in Section VII-A.

Figs. 6–8 report outcomes for total realized household load on day D+1 when the IDSO sends controlled retail price signals to households to achieve a 0.5MW target peak load reduction on day D+1. For comparison, load outcomes resulting under the flat retail price $\overline{\pi}$ with no IDSO price control are also reported. All households have the same SQT, either all Low, all Medium, or all High.

Fig. 9 reports the specific retail price signals sent by the IDSO to households in a power usage state on day D+1 for each of the three SQT cases reported in Figs. 6–8. The strong variation seen in these retail price signals across the three different SQT cases indicates that careful consideration should be given to household structure quality in peak-load reduction studies, particularly if retail price volatility is a concern.

D. Test Case 3: IDSO Load Matching Capabilities

This subsection reports outcomes for test cases in which the system goal of an IDSO managing a Five-Step TES Design for households on day D is to match total household load on day D+1 to a target load profile.

As depicted in Fig. 3, the IDSO functions at a substation of a 123-bus grid. The IDSO participates in a wholesale Day-Ahead Market (DAM) operating over a transmission grid that connects to the distribution grid at this substation.

On each day D the IDSO submits a fixed demand bid into the DAM consisting of a forecasted 24-hour profile for total household load during day D+1. On day D+1 the IDSO attempts to ensure actual total household load does not deviate from the fixed demand bid it submitted into the DAM on day D. Any such deviations must be settled using real-time market locational marginal prices on day D+1, which is risky because these prices tend to be highly volatile.

More precisely, the IDSO on day D+1 uses its continually refreshed vector AggBid of household aggregate bid functions

[18] A *price-step* is the time interval corresponding to Step 4 for some iteration of the bid-based TES design; see Section VII-B. As detailed in Section VII-A, the length of each price-step (i.e., the inverse of the price signal rate) is set equal to Δt = 300s (5min) for all test cases reported in this study.

[19] Specific characterizations for the Low, Medium, and High SQTs used for this test case are provided in [1, Apps. D and E].

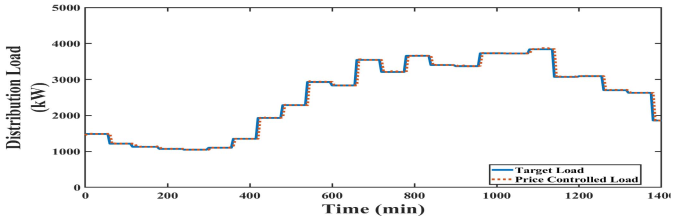

Fig. 10. IDSO's ability to use controlled retail prices to match total household load on day D+1 to a target load profile, given by the IDSO's fixed demand bid submitted into a day-ahead market on day D.

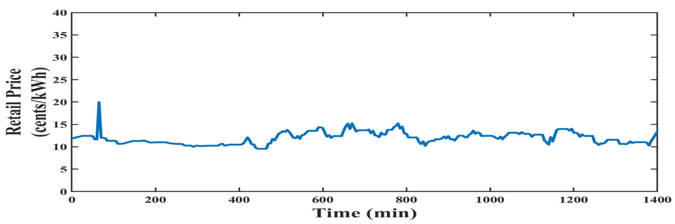

Fig. 11. The retail price signals sent by the IDSO on day D+1 to households in a power usage state to match total household load to the IDSO's day-D DAM fixed demand bid, depicted as the target load profile in Fig. 10.

to calculate and send retail price signals to households that ensure realized total household load on day D+1 matches the fixed demand bid the IDSO submitted into the DAM on day D. At the start-time for any price-step k on day D+1, AggBid consists of two distinct aggregate bid functions: one constructed from the optimal bid functions submitted by households in a power usage state (identified by their submission of positive cut-off prices); and a second one constructed from the optimal bid functions submitted by households in an ancillary service state (identified by their submission of negative cut-off prices).

Fig. 10 reports load-matching outcomes for a case in which the distribution grid is populated by a mixture of households with Low, Medium, and High SQTs.[20] All households have the same maintained Resident Type with a marginal utility of money $\mu = 1$ (utils/¢). As seen, the IDSO is successfully able to use retail price signals on day D+1 to match total household load to the load profile it submitted to the day-D DAM as its fixed demand bid.

The retail price signals used by the IDSO to achieve the good load matching in Fig. 10 are shown in Fig. 11. Note that all of these retail price signals are positive, indicating the IDSO is not making any use of ancillary service to achieve its load matching goal.

As a second load-matching test case, suppose the IDSO instead submits into the day-D DAM the fixed demand bid (load profile) depicted in Fig. 12. Once again, as seen, the IDSO is successfully able to use retail price signals on day D+1 to match total household load to this target load profile.

The retail price signals used by the IDSO to accomplish the good load matching depicted in Fig. 12 are shown in Fig. 13. In contrast to the earlier load-matching test case, it is seen that the IDSO must now actively use ancillary service (power absorption) bids in order to achieve its load-matching goal.

[20]The SQT of each household connected at each grid bus is configured as Low, Medium, or High with probabilities (1/3, 1/3, 1/3).

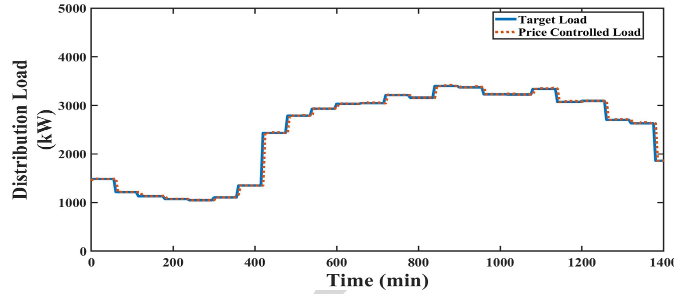

Fig. 12. IDSO's ability to use controlled retail prices to match total household load on day D+1 to a different target load profile, i.e., a different fixed demand bid submitted into the day-D DAM.

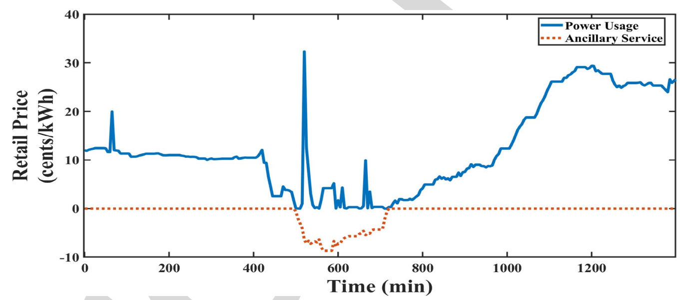

Fig. 13. The positive and negative retail price signals communicated by the IDSO to households on day D+1 to match total household load to the target load profile depicted in Fig. 12.

Specifically, the target load profile sharply increases starting around hour H7 (minute 420) on day D+1. To match actual load to this upward shift, the IDSO has to send negative retail price signals to households in an ancillary service state to induce additional power usage. Recall that the magnitude of a negative retail price signal denotes the price a household in an ancillary service state will receive in compensation for any supplied ancillary service (power absorption).

However, in attempting to interpret more fully the retail price movements depicted in Fig. 13, it is essential to keep in mind they arise from a complicated underlying causal process. Specifically, they depend on dynamic nonlinear interactions among external forcing terms (e.g., grid voltage and weather conditions), house and appliance attributes, resident net benefit and bid functions, thermal dynamic relationships, IDSO system goals and constraints, and past price-induced HVAC ON/OFF control actions. For example, the *rising* retail prices observed subsequent to hour H12 (minute 720) reflect the IDSO's need to *reduce* household power usage demand *down* to the IDSO's target load levels, given all that has gone before.

IX. Concluding Remarks

This study formulates methods to facilitate the development and evaluation of bid-based transactive energy system designs starting from a careful consideration of local customer goals and constraints. The basic idea is to ensure that system requirements respect private requirements, as far as physical reliability permits, so that voluntary customer participation is maintained.

For concreteness, attention is focused on distribution systems populated entirely by households. The optimal form

TABLE I
HOUSEHOLD WELFARE: VARIABLES, FUNCTIONS, & PARAMETERS

	Description
$\widehat{\mathrm{C}}^*(n)$	Forecasted net cost (¢) at the start of control-step n
$\widehat{\mathrm{G}}^*(n)$	Forecasted comfort (utils) at the start of control-step n
$\widehat{\mathrm{NB}}^*(n)$	Forecasted net benefit (utils) at the start of control-step n
X_n^{s}	Ancillary service provision state for n
X_n^{u}	Power usage demand state for n
μ	Marginal utility of money (utils/¢)
$-\Pi^*(X_n^s)$	Min acceptable payment (¢/kWh) for HVAC ancillary service in state X_n^{s}
$\Pi^*(X_n^u)$	Max willingness to pay (¢/kWh) for HVAC power usage in state X_n^{u}

TABLE II
HOUSE THERMAL DYNAMICS: DERIVED (NON-BASE) PARAMETERS

	Description
C_a	Heat capacity (Btu/^{o}F) of the inside air mass
C_m	Heat capacity (Btu/^{o}F) of the inside solid mass
H_m	Thermal conductance (Btu/[h-^{o}F]) between inside air & solid masses
U_a	Thermal conductance (Btu/[h-^{o}F]) between internal & external air masses
P_{fan}	Power consumption (kW) of the 1-speed HVAC air-circulation fan if ON during n

of household bids for thermostatically-controlled power usage and ancillary service provision is first deduced from general dynamic programming principles. Specific quantitative forms of these bids are then derived as functions of base parameters characterizing household thermal dynamic and welfare attributes. It is then shown how these optimal bid forms can be built into a bid-based transactive energy system design, as a starting point, so that subsequently considered system goals and constraints are well aligned with local customer goals and constraints.

This customer-centric approach contrasts with currently common approaches to power system design that start by presupposing fixed system goals, such as peak-load constraints, reserve requirements, and load shedding policies based on administratively pre-set value-of-lost-load specifications. This prioritization of administratively determined system goals prevents assurance that the resulting designs are truly optimal from a social welfare point of view.

The test cases reported in this study provide preliminary evidence for the feasibility and desirability of customer-centric bid-based transactive energy system design. Future studies will push further and harder. Particular attention will be focused on the management of such designs by independent distribution system operators operating as linkage entities at transmission and distribution system interfaces. A key issue to be examined is the ability of such designs to support the creation of new customer revenue streams through the provision of flexible dependable ancillary services to wholesale power markets.

TABLE III
HOUSE THERMAL DYNAMIC FACTORS AND VARIABLES

	Description
f_i, f_s, f_{ac}	Heat gain (decimal %) from $Q_i(t)$, $Q_s(t)$, and $Q_{\mathsf{hvac}}(t)$ to $Q_m(t)$ at each time t
K	Conversion factor (3412Btu/[h-kW]) that converts kW to Btu/h
K_h	Conversion factor (1h/3600s) that converts seconds s to hours h (hence 1/h to 1/s)
$K^*(n)$	Coefficient of performance (Btu/[h-kW]) for the HVAC system at time n^{s}
n	Control-step $n = [n^{\mathsf{s}}, n^{\mathsf{e}})$, where $n^{\mathsf{s}} = t_0 + n\Delta\tau$ and $n^{\mathsf{e}} = t_0 + [n+1]\Delta\tau$
$P^*(n)$	Total HVAC power consumption (kW), including fan, if HVAC is ON during n
$P^*_{\mathsf{hvac}}(n)$	Power consumption (kW) of main HVAC unit if ON during n
$Q^*_a(n)$	Total heat flow rate (Btu/h) to inside air mass at time n^{s}
$Q^*_{\mathsf{hvac}}(n)$	Heat flow rate (Btu/h) from the HVAC system (including fan) if ON at time n^{s}
$Q^*_i(n)$	Heat flow rate (Btu/h) from internal non-HVAC equipment/occupants at time n^{s}
$Q^*_m(n)$	Total heat flow rate (Btu/h) to inside solid mass at time n^{s}
$Q^*_s(n)$	Heat flow rate (Btu/h) from solar radiation at time n^{s}
t_0	Simulation start-time (granularity of secs)
$T^*_a(n)$	Inside air temperature (^{o}F) at time n^{s}
$T^*_m(n)$	Inside mass temperature (^{o}F) at time n^{s}
$T^*_o(n)$	Outside air temperature (^{o}F) at time n^{s}
$u^*(n)$	Binary 0-1 variable denoting OFF/ON HVAC control action for control-step n
$\Delta\tau$	Length (seconds) of each control-step n
$\pi^*(n)$	Retail power price (¢/kWh) at time n^{s}

NOMENCLATURE

Tables I-III provide symbols and descriptions for the variables, function, parameters, and conversion factors explicitly appearing in the quantitative representations for household thermal dynamics and welfare presented in Sections IV–V.

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