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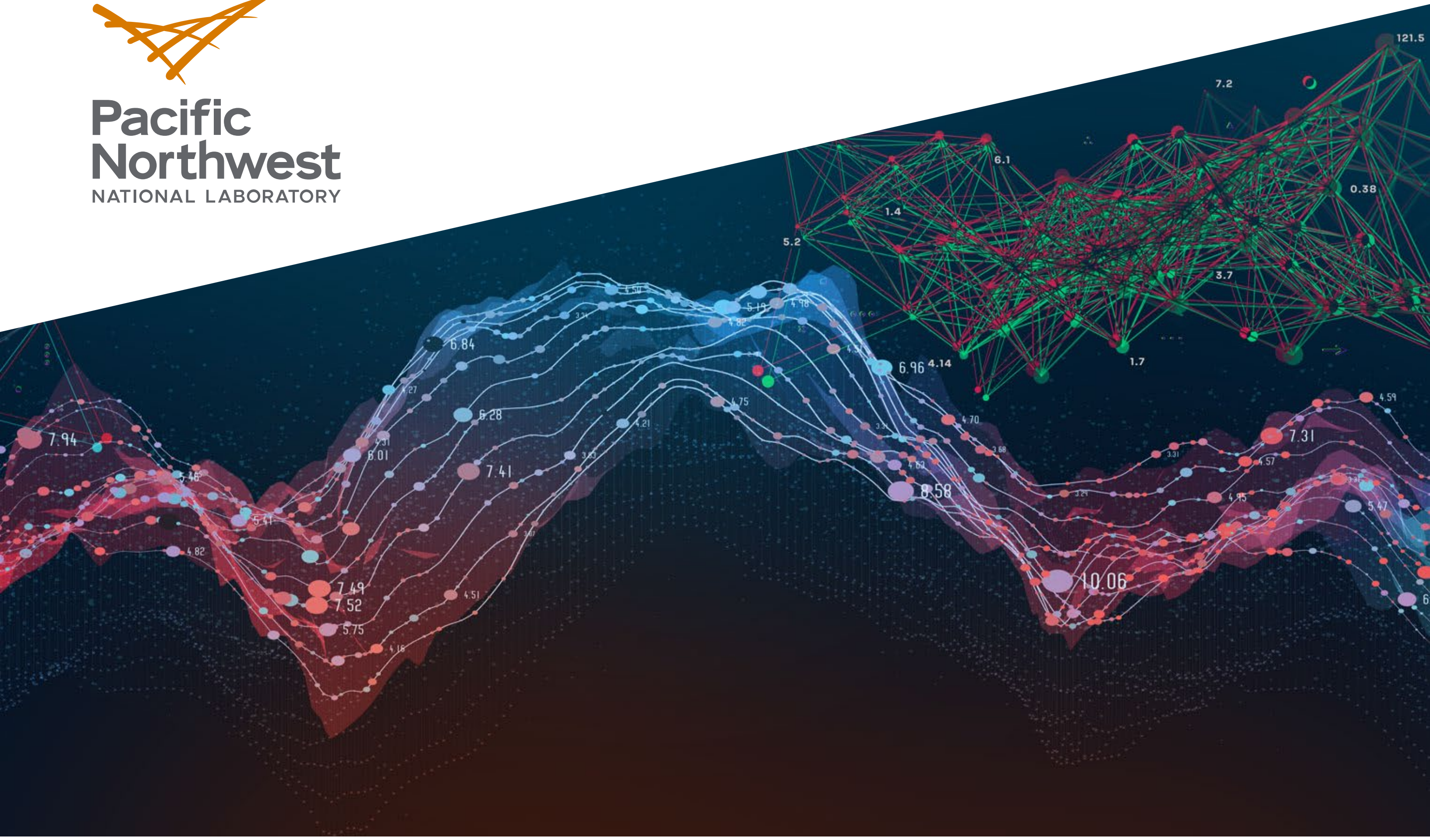

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DSO+T: Transactive Energy Coordination Framework

DSO+T Study: Volume 3

January 2022

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U.S. DEPARTMENT OF ENERGY

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Abstract

This report describes a transactive energy coordination scheme designed to integrate into existing day-ahead and real-time wholesale energy markets. This scheme was evaluated in the Distribution System Operator with Transactive (DSO+T) study to assess the engineering and economic performance of the transactive energy coordination of a large-scale deployment of distributed energy resources (DER). Transactive agents were developed for a range of DERs (heating, ventilation, and air conditioning units, water heaters, batteries, and electric vehicles) that optimize flexibility over a 48-hour horizon and adjust their strategy in response to changes in real-time prices. A transactive energy coordination scheme, executed by a DSO retail market operator, aggregates these DER bids from participating customers and clears them against a DSO supply curve using a double-auction market mechanism. The process of constructing the price-quantity DSO supply curve includes distribution-level transportation constraints (for example, substation congestion limits) and forecast locational marginal price of the DSO's connected transmission node. The resulting day-ahead and real-time quantities are then bid into a competitive wholesale market operated by an independent system operator. This report also details additional capabilities for proper marketplace simulation such as wholesale price, weather, and load forecasting. The report concludes with a discussion of lessons learned and key design features required to ensure successful operation.

Summary

The purpose of the Distribution System Operator with Transactive (DSO+T) study is to simulate and analyze how a distribution system operator (DSO) can engage price-responsive distributed energy resources (DERs) by using a coordination strategy based on transactive energy mechanisms. This study seeks to compare two DSO-coordinated transactive cases (one with flexible loads, the other with batteries) against a business-as-usual system operation approach that only uses traditional system generation control resources. These three cases are analyzed over two renewable energy scenarios, the first with moderate levels (<20%) of annual renewable generation, the second with high levels of annual renewable energy production (~40%).

This evaluation necessitated the detailed development and implementation of a transactive energy coordination scheme that could be used by a DSO to aggregate transactive bids from a large number of customers with a wide range of DERs and bid the result into the day-ahead and real-time energy markets of a competitive wholesale market. In addition, the scheme is able to manage distribution-level constraints such as substation or feeder congestion. Detailed transactive agents were developed for a range of DERs with operational flexibility including heating, ventilation, and air conditioning (HVAC) units, water heaters, batteries, and electric vehicles. This report details the overall methodology of this transactive energy coordination scheme. It focuses on the design of a DSO-managed transactive retail marketplace that coordinates with customer-managed assets and includes the design of the DSO's representation of the flexibility of these resources through interactions with a representative wholesale marketplace. It is one of five reports documenting the DSO+T study: Summary Report, Integrated System Simulation, Transactive Coordination Framework, Valuation Methodology and Economic Metrics, and Study Results.

The DSO-managed transactive retail marketplace is designed to integrate with existing competitive wholesale energy markets. In this study, it was assumed that an independent system operator runs competitive hourly day-ahead and 5-minute real-time markets. DSOs provide their day-ahead and real-time load forecasts into this market. In addition, merchant generators also provide their performance (marginal production price) and operating constraints information to the wholesale market operator. A security-constrained unit commitment and dispatch process is used to schedule and dispatch the generation fleet day ahead and in real time, thereby determining the locational marginal price for electricity at each transmission node. These prices inherently include the impacts of transmission-level congestion.

The DSO develops its wholesale demand bid by running a transactive retail marketplace for participating customers who have price-responsive DERs. (The results of this marketplace are combined with the demand forecast of nonparticipating customers to determine the total DSO demand bid.) The retail marketplace has an hourly forward market with a 48-hour lookahead window that aggregates participating customer hourly price-quantity demand bids based on forecast wholesale energy prices over the 48-hour horizon. These bids are cleared using a double-auction process and updated price and cleared quantity forecasts are provided at the next hour. This repeats every hour ensuring the convergence of marketplace coordination and resulting quantities as the wholesale day-ahead market closure approaches. At 10 a.m. the DSO submits its financially binding day-ahead demand bid (including forecast uncertainty) to the wholesale market operator. The hourly, sliding 48-hour lookahead retail marketplace operation then continues forward.

In parallel with the retail forward market, is a real-time energy market. The retail real-time bid is created by providing the 5-minute prior real-time price to all participants allowing them a final adjustment to their evolving hourly response strategy. The DSO's retail price-quantity supply curve includes distribution constraints (such as substation capacity limits) ensuring that the formulated retail price signal supports the management of local congestion.

To determine the response strategies of participating DERs, transactive agents were developed for HVAC units, water heaters, electric vehicles, and batteries. These DER agents have four common elements: an asset model that enables the agent to estimate its physical behavior over the next 48 hours; a scheduling module that determines the optimal response given forecast retail prices and customer preferences and constraints (e.g., comfort); a retail bidding module that develops the required price-quantity bid curve; and a control mapping module that converts the desired demand strategy into asset-specific setpoints, such as thermostat settings or vehicle charging patterns. As mentioned above, each DER agent updates its 48-hour forecast every hour and revises its actual real-time strategy in the 5-minutes prior to the interval in question. All agents subscribe to common price and weather forecasting modules ensuring that forecast uncertainty is included in the analysis.

This report concludes with a discussion of lessons learned and areas warranting future research. The field representative fidelity of this simulation enabled a thorough verification of the performance of the transactive marketplace and its interactions with tens of thousands of price-responsive DER assets. In doing so, many requirements for the accurate and stable operation of this marketplace were identified. In particular, asset agents need to address discontinuities that can arise as hourly, forward market strategies move to 5-minute, real-time market interactions. Also, the aggregation of bids from a large number of participating agents needs to be computationally efficient, but not diminish the fidelity of the resulting aggregate retail price-quantity curve. Insufficient sampling can result in non-trivial errors in cleared quantity.

The study reveals many areas for future research. While it demonstrated the stable and successful operation of a transactive market with representative levels of forecast uncertainty, questions arise about the level of forecast accuracy required for the system to operate in a stable manner. How could superior price and weather forecasts improve performance of the system? How well does the system respond to irregular events or situations? In addition, the implementation of an intraday hourly wholesale market would be expected to provide more frequent price information updates to the retail market, improving the effectiveness of its response. The value of enhanced response from these flexible resources is an area of future research needs.

Acknowledgments

This project was supported by the Department of Energy, Office of Electricity, Advanced Grid Research and Develop Program. The authors would like to thank Chris Irwin for his support and contributions to the DSO+T study.

Acronyms and Abbreviations

AMES	Agent-Based Modeling of Electricity Systems
BAU	business-as-usual
DER	distributed energy resource
DOE	Department of Energy
DSO	distribution system operator
DSO+T	Distribution System Operation with Transactive
ERCOT	Electricity Reliability Council of Texas
EV	electric vehicle
HVAC	heating, ventilation, and air conditioning
ISO	independent system operator
LMP	locational marginal price
LSE	load-serving entity
PNNL	Pacific Northwest National Laboratory
SCED	security-constrained economic dispatch
SCUC	security-constrained unit commitment
SOC	state of charge
SOHE	state of heat energy
TESP	Transactive Energy Simulation Platform
TEV	transactive electric vehicle
V1G	Variable Vehicle Charging from the Grid
V2G	Variable Vehicle Charging and Discharging from the Grid

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1 Transactive Marketplace Introduction

1.1 Introduction to the DSO+T Study

The Distribution System Operator with Transactive (DSO+T) study simulates and analyzes how a distribution system operator (DSO) can engage flexible distributed energy resources (DERs), such as air conditioners, water heaters, and batteries, in the operation of the electric power system by using a coordination strategy based on transactive energy mechanisms (GWAC 2019; Hammerstrom et al. 2008). This study is designed to:

- Produce a design of a DSO transactive network capable of coordinating DERs deployed at scale to produce benefits at both the distribution and bulk system levels.
- Test the design and estimate the benefits of a regional deployment at scale for a range of potential future grid scenarios using the valuation (Hammerstrom, Makhmalbaf and Marinovici 2017) (Hammerstrom 2016) and co-simulation (Mukherjee et al. 2020; Huang et al. 2018) frameworks developed previously for the U.S. Department of Energy's Transactive Systems Program.
- Issue the simulation and valuation framework to industry as an open challenge to the transactive energy community to develop and improve their designs in preparation for field experiments.

The DSO+T study involves comparing the engineering and economic performance of business-as-usual (BAU) cases representing today's distribution utilities with fixed-price rates for all customer classes and no active participation of price-responsive DERs with that of transactive cases in which the distribution utilities have evolved into DSOs that reflect their operational costs in the form of local retail markets for energy. It assumes most customers have installed price-responsive DERs such as batteries, electric vehicles (EVs), or flexible air conditioning and water heating systems, which interact with forecasts of day-ahead and real-time dynamic prices and bid into the retail markets that seek to discover optimal and equitable real-time prices in a distributed fashion characteristic of transactive energy systems.

A family of reports documents the DSO+T study. The primary results are summarized in Volume 1, Main Report (Reeve, Widergren, et al. 2022c), with considerable additional detail on the results of the analysis provided in Volume 5, Study Results (Reeve and et al 2022b). The instantiation of a large, multiscale, annual, time-series co-simulation that is the foundation of the analysis, representing a nationally representative generation fleet, transmission system, and distribution system including retail customer building characteristics and DERs, is described in Volume 2, Scenario and System Definition Report (Reeve, Singhal, et al. 2022a). Volume 4 (Pratt, et al. 2022) describes the valuation and economic metrics used to access the value of adopting the DSO+T strategy for all the primary stakeholders by comparing changes in various metrics between any two cases of the study. This document (Volume 3) describes the design of the transactive retail marketplace and DER control agents and their integration into a competitive wholesale market.

Figure 1 shows a high-level view of the scope of the design of the DSO+T study's market-based coordination mechanism. It models a typical independent system operator (ISO)-style market at the wholesale level and introduces a DSO using a retail market to engage DER flexibility operated by the DSO's customers.

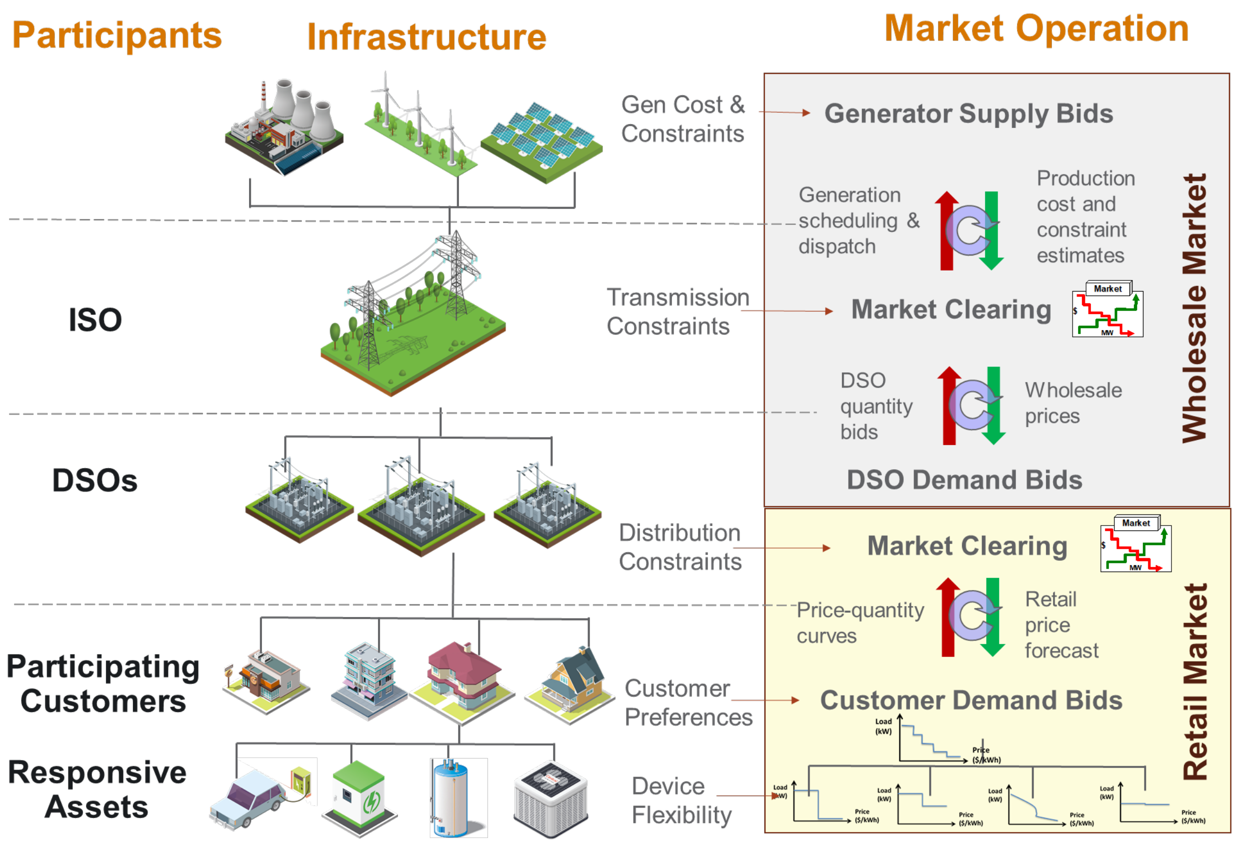


Figure 1. Summary of the integrated wholesale and retail market operation.

The remainder of this section overviews the marketplace objectives and structure. This is followed by a review of prior relevant efforts and a summary of the remainder of the report structure.

1.2 Purpose and Objectives

To study the impact of large penetrations of flexible DER requires an approach to coordinating the operation of these resources in conjunction with the bulk electricity system. The DSO+T study models the DSO as an aggregator of DER assets operated by customers in its jurisdiction. The DSO uses a transactive energy approach to engage customer decisions in the operation of their assets. This delegative style of coordination allows customers to individually represent their priorities for energy use to meet their needs. The DSO accomplishes this by running a retail marketplace that resolves the value exchanges of customers with the dynamic prices for energy arising from a typical ISO-style wholesale market.

This volume of the report describes the design of the wholesale and retail marketplaces to engage large penetrations of DER under the scenarios investigated in the DSO+T study. It explains the participants in the wholesale and retail markets, design of the market mechanisms, interfaces of the participants to the markets, and the decision-making algorithms used by each participant as they interact in the markets.

The approach taken in the study is the result of many design decisions about the market structure, the economic equilibrium-seeking mechanism, and the models of equipment and customer behavior involved in participant decision-making. As such, it does not portray the definitive answer to the coordination problem but poses a rational approach to one way that this coordination can take place. In the process, the design indicates the feasibility of a transactive energy approach to coordinate vast numbers of DERs.

The desired result of this transactive energy coordination framework design is to demonstrate a distributed decision-making approach that works stably in simulation and provides insights into the impacts of DER integration on overall grid engineering and economic performance. An additional outcome is demonstration that beyond feasibility such an approach has technical and economic characteristics amenable to the field realization.

1.2.1 Measures of Proper System Operation

The design of the transactive energy coordination framework was used to implement the co-simulation environment for conducting the DSO+T study. Aspects of proper system operation are revealed through simulation runs that test the market resolution logic and the participant market interactions that yield reasonable operating results over the variety of system scenarios (moderate and high renewables, batteries, and flexible loads) investigated in the study. Each scenario involves runs that span all seasons of the year.

One measure of proper operation is the ability to find a solution (equilibrium) in every market cycle. The various markets (day-ahead and real-time across the wholesale, and retail marketplaces) need to resolve to a series of market-clearing prices that balance supply and demand in the system. The algorithms used in the agents' decision-making process were evaluated under normal operating conditions to see that price-quantity bids in lookahead day-ahead markets had a solution and that changes of bids to previous positions taken for the same hours diminished in successive market clearings. In addition, the real-time market clearings were observed to be near the day-ahead positions, unless conditions changed significantly (e.g., due to weather forecast errors or equipment outages).

These reasonability measures indicate that decision-making appears rational and directionally coherent from an individual participant and systemic point of view. The measures are imprecise when it comes to proofs of optimality. The design process itself indicates many areas where the models, decision-making approach, and processes used can be improved. Many of these items are mentioned in Section 5.

1.3 Marketplace Overview

The transactive energy coordination framework for managing the operation of controllable equipment in the DSO+T study relies on value exchanges for scheduled energy among wholesale marketplace participants in the bulk system and value exchanges for energy among retail marketplace participants in the distribution system. The interactions between these two tiers are managed by DSOs who straddle the line between wholesale and retail marketplaces as participants in each.

Figure 2 shows a model of the participants in the bulk and distribution systems. The figure depicts a third tier to describe the participants in the customer systems that interact with the retail marketplace.

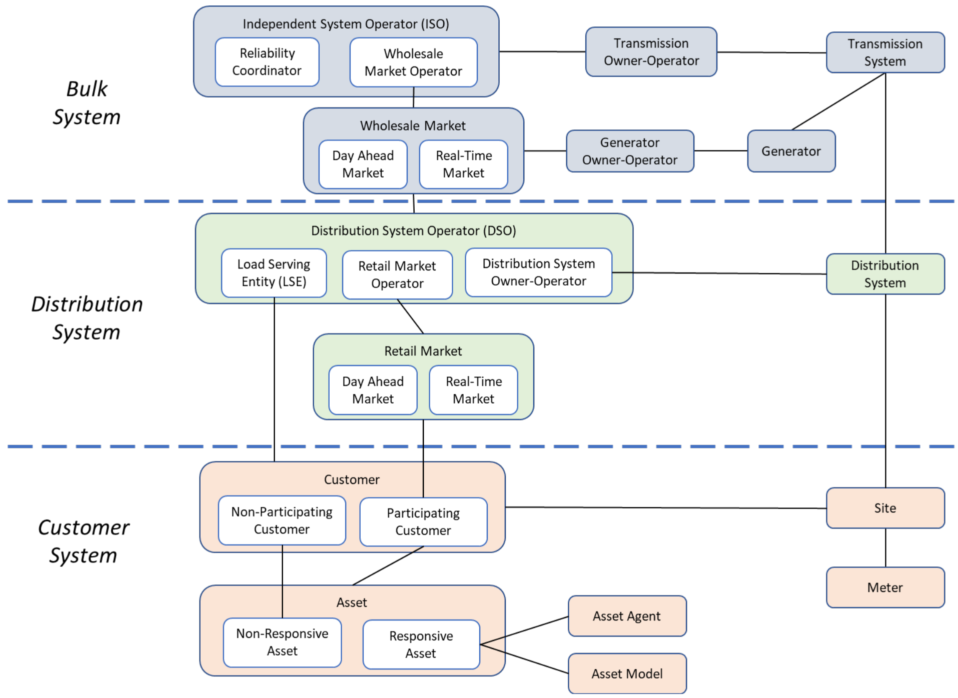


Figure 2. Overview of system marketplace with participants and assets.

Figure 3 depicts a high-level process flow of the coupled wholesale-retail marketplaces with day-ahead and real-time markets. The DSO plays a crucial role in interacting with both the wholesale and retail marketplaces and translating the value signals between them. Details about the information flow, the timing, and the logic being executed within the market processes are presented in subsequent sections of the report.

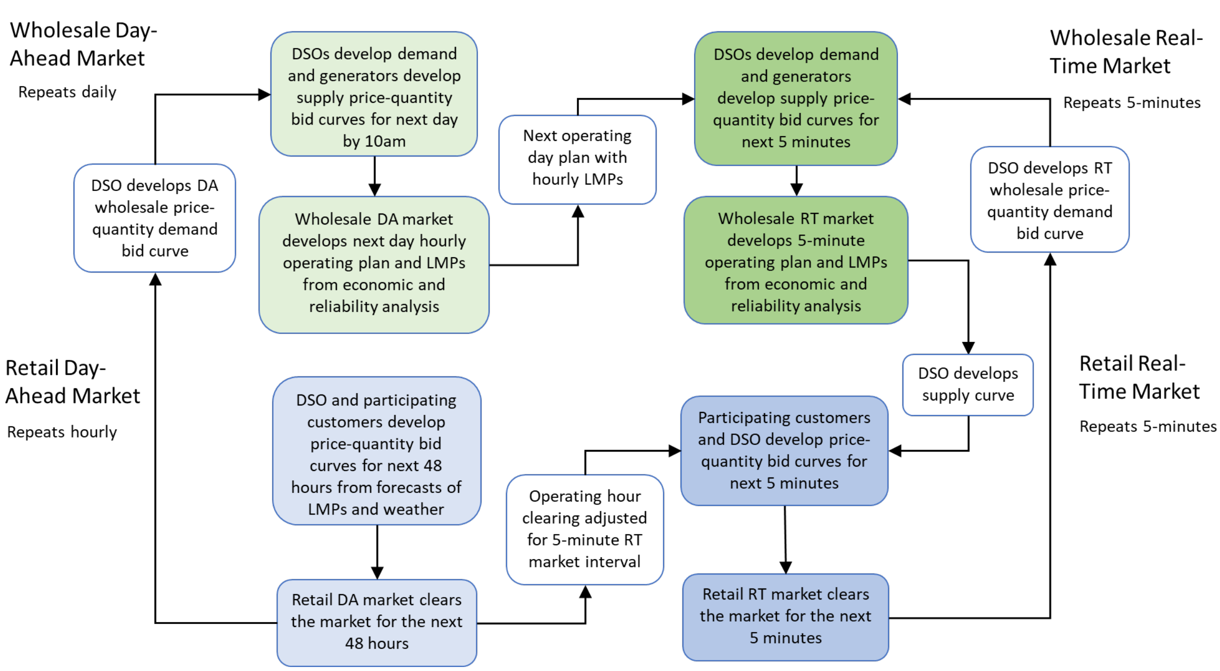


Figure 3. Overview of the coupled wholesale and retail market process.

1.3.1 Wholesale Marketplace

The wholesale market is overseen by an ISO who acts as a reliability coordinator to manage the reliability services of the bulk system and a wholesale market operator who manages the wholesale day-ahead and real-time markets. Transmission owner-operators manage the transmission system as overseen by the ISO. Generator owner-operators manage the bulk generation fleet and interact with the wholesale markets to sell energy that is delivered through the transmission system. DSOs represent the customers and reliable operation of the distribution system in their interactions with the wholesale markets.

In the DSO+T study, each generator and DSO is connected to one transmission node in the system. The wholesale day-ahead market resolves a next day, 24-hour period of scheduled energy at 10 a.m. every day. The day-ahead market value object (the good traded) is 24 hourly blocks of energy covering midnight to midnight. The DSOs present their load forecasts for each of these 24-hour delivery periods and the generators present their supply bids for the same period. The wholesale day-ahead market takes input from security-constrained unit commitment (SCUC) and security-constrained economic dispatch (SCED) algorithms to ensure the reliability constraints from the generation fleet are met. In addition, transmission delivery constraints are reflected in optimization routines that calculate locational marginal prices (LMPs) at each transmission node. When a delivery constraint occurs, LMPs provide price incentives for generators to alter their generation up or down to relieve the constraints. The market uses a double-auction mechanism to determine the clearing price and the amount of energy committed from each generator to meet the forecasted demand from the DSOs. In the wholesale market, the system operator signals the generator operators to move generators up or down based on the LMPs and the SCED.

The wholesale real-time market involves the same participants submitting generation price-quantity bids and demand forecasts to correct their positions in the day-ahead market based on the latest information. The real-time market runs every 5 minutes to resolve the next 5-minute delivery period. The value object traded is a 5-minute block of energy from each participant. LMPs are also calculated for the wholesale real-time market and uses a double-auction mechanism to resolve the transactions. Generators are dispatched according to the resulting energy schedules. DSOs plan to absorb energy per their energy schedules. Each generator owner-operator's and DSO's performance is measured at the transmission node to which they are connected. Discrepancies from planned operation to actual operation are resolved at the wholesale real-time LMP for each delivery period.

1.3.2 Retail Marketplace

The DSO acts as a load-serving entity (LSE) for its customers, a distribution system owner-operator to manage the distribution system, and a retail market operator to coordinate customers with price-responsive assets, called participating customers. The retail market operator uses a double-auction mechanism to resolve day-ahead and real-time markets trading scheduled energy value objects with participating customers. The LSE forecasts the load of nonparticipating customers, while the demand of participating customers comes from their planned interactions with the retail day-ahead and real-time markets. The DSO uses this information for input into the wholesale marketplace.

In the DSO+T study, each distribution system owner-operator manages the load at one transmission substation. All the DSO's customers are connected through distribution circuits to that substation. The substation's delivery constraints are reflected as supply limits to the retail marketplace. The retail day-ahead market resolves 48 hourly delivery periods every hour. As the hour advances, a sliding window of 48 new delivery periods is resolved. The retail day-ahead market receives a supply curve of 48 hourly delivery periods from the DSO based on a wholesale price-quantity curve forecast for its transmission node. The supply curve includes adjustments from wholesale-to-retail prices and incorporates the substation delivery constraint. Participating customers aggregate their responsive assets and forecast the needs of the nonresponsive assets as 48-hour energy price-quantity curves submitted to the retail day-ahead market. At 10 a.m. each day, the DSO uses the latest retail day-ahead 48-hour lookahead market to extract the 24 hours that correspond to the wholesale day-ahead market period to derive its wholesale demand bid.

The retail real-time market runs every 5 minutes to resolve the next 5-minute delivery period. The value object traded is a 5-minute block of energy from each participant. The DSO submits a supply curve based on the wholesale real-time market clearing (with retail adjustments), while every 5 minutes the participating customers submit their price-quantity bid curves. The real-time market results correct the day-ahead position taken by each participating customer while incorporating the latest marketplace information including weather and load forecasts. Each customer’s energy use for every 5-minute period is measured by an interval meter at the point where the customer’s site connects with the distribution system. Bills are calculated using the fixed-rate agreement for nonparticipating customers or the dynamic-rate agreement for participating customers.

1.4 Inspiration for Transactive Energy Coordination Framework

Pacific Northwest National Laboratory (PNNL) has researched transactive energy coordination since the turn of the millennium including the design, simulation, and field deployment of double-auction markets for coordinating DER connected to distribution circuits in Washington State (Hammerstrom, et al. 2007) and Ohio (Widergren et al. 2014). The real-time 5-minute market used in these projects was extended in the DSO+T study to include a day-ahead market to allow the resources to better prepare for forecasted weather and market conditions. It also allows the DSO, as aggregator of the flexibility of these resources, to better interact with the wholesale marketplace. To accomplish this, refinements were made to the responsive asset agents (e.g., heating, ventilation, and air conditioning [HVAC] units, EV chargers, and electric water heaters) and the simulation of their physical behavior. In addition, new simulation models of equipment (e.g., batteries) and buildings were developed along with their agents.

Other transactive mechanisms, such as bilateral markets (Cazalet, Kohanim and Hasidim 2020) or consensus coordination schemes (Katipamula et al. 2017) are plausible approaches that have also been field demonstrated. The familiarity with the double-auction market design, the simulation tools already in place, and experience with the agent decision-making strategies contributed to the coordination framework adopted for the study.

A design requirement of the DSO+T study is to integrate DER flexibility into a bulk electric system using market incentives that are familiar to wholesale energy markets operating today in the United States. To do this, we treat each DSO as an aggregator of the flexibility offered by its customers. This allows the price-sensitive demand represented by the DSO to participate on a more similar footing to the price-sensitive supply represented by the generator owner-operators in the wholesale market. In the BAU case, the DSO relies strictly on load forecasts of its customers to represent demand to the wholesale market. There is no flexibility offered from price-sensitive responsive assets. The DSO+T study uses the Agent-Based Modeling of

Electricity Systems (AMES) wholesale market simulation software (Li and Tesfatsion 2009) to simulate the wholesale marketplace with DSO bidding.

The shape that DSOs and flexibility aggregators will take is emerging in several different forms. To perform the DSO+T study, the project engaged experts investigating DSO-related business and regulatory structures (De Martini, Kristov and Schwartz 2015). The result was a simplified and streamlined organization of a not-for-profit entity with the objectives of reliably and efficiently operating a distribution system and enabling customer's DER access to bulk electric system and DSO value streams. Transactive energy coordination is a natural fit for translating these value streams into operational incentives for customers with responsive assets. While the organizations that aggregate DER flexibility will take different forms, the simplified design used for the DSO+T study supports the primary goal of linking bulk-level and distribution-level value streams with DER flexibility to enable an overall coordination framework that seeks optimal behavior from the marketplace participants.

1.5 Report Structure

The remainder of this report provides a description of the marketplace (Section 2) and its corresponding design (Section 3). Section 4 then discusses the specific strategies and implementations used by market operators and participants. These sections have dedicated treatments for both the wholesale and retail markets and their participants. The report concludes with a summary of lessons learned on agent and market design through the execution of this study and highlights valuable future research directions.

2 Marketplace Description

This section describes the wholesale and retail markets, their participants, and the interactions that take place to integrate them using the appropriate components of the DSO concept.

2.1 The Wholesale Marketplace

The intent of the wholesale marketplace design for the DSO+T study is to represent the core features found in several ISO markets in the United States including the Midwest, New York, New England, and the mid-Atlantic region. The characteristics include coordinated operation of day-ahead and real-time scheduled energy markets and management of transmission constraints using LMPs.

Researchers at Iowa State University developed the AMES Wholesale Market Test Bed (Li and Tesfatsion 2009) using the business practices manuals from these markets to create a simulation of “a centrally administered wholesale power market operating through time over an alternating current transmission grid.” The open-source AMES simulator is linked with the Transactive Energy Simulation Platform (managed at PNNL) using co-simulation tools to support the integrated wholesale/retail marketplace environment required for the DSO+T study.

The AMES simulator uses a direct current optimal power flow (a linearized version of the alternating current power flow that assumes a flat system voltage profile) to calculate LMPs based on the demand and supply market tenders from traders that are simulated as independent agents in a multi-agent computational environment. Figure 4 shows the main players interacting in the wholesale marketplace. Each player and their interactions are introduced in the following subsections.

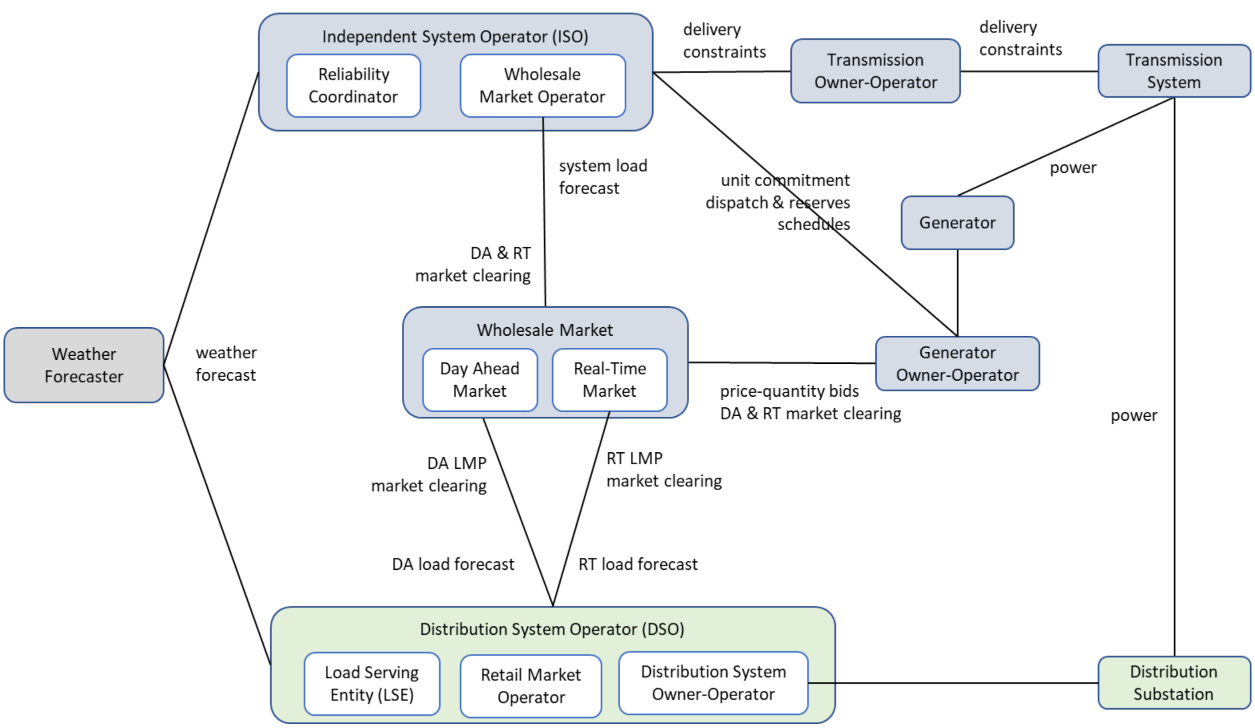


Figure 4. Wholesale marketplace participants and interfaces.

2.1.1 Types of Participants

This section describes the types of wholesale marketplace participants used in the DSO+T transactive coordination framework. The way that market participants interface with the wholesale market is explained in Section 3.1, while the internal agent logic is explained in Section 4.1.

ISO: Reliability Coordinator and Wholesale Market Operator

The wholesale market is managed under the auspices of an ISO with two roles: the reliability coordinator and the wholesale market operator. The reliability coordinator is responsible for reliable operation of the interconnected system including coordination with neighbors. The wholesale market operator manages the market where participants trade.

The objective of the ISO is to ensure reliable operation of the system and seek operational efficiency of the wholesale market under constraints imposed for reliability. To do this, the wholesale market operator runs a day-ahead market daily that is settled using LMPs for each of the 24 hours in the next day. Coupled with the wholesale day-ahead market is a real-time market that runs every 5 minutes. The real-time market is also settled using LMPs. Differences in the supply or consumption of energy between positions taken in the wholesale day-ahead market are corrected with the unit price of energy resolved in the wholesale real-time market for the corresponding 5-minute intervals in the day-ahead hour.

Transmission System Owner-Operator

The transmission system owner-operator is responsible for operating and maintaining the transmission infrastructure. It provides information about the capacity limits of transmission system equipment, such as lines and transformers. These limits are used by the reliability coordinator in representing the constraints of operation to the marketplace.

Generator Owner-Operator

Two types of traders interact with the wholesale market, generator owner-operators and DSOs. For the DSO+T study, a generator owner-operator manages one generator that is connected to a bus in the transmission system. The generator owner-operator's objective is to maximize net earnings through its market participation. It places tenders for the supply of energy from its generator into the wholesale market. To determine its offering, it models the costs of supplying electricity at various power levels. The population of generator owner-operators does not change over the course of the study.

DSO

A DSO manages the delivery of power into a distribution system that is connected to a bus in the transmission system. The DSO is a complex entity that performs the roles of an LSE, a distribution system owner-operator, and a retail market operator. These roles are described in Section 2.2.1.2. With respect to the wholesale marketplace, a DSO represents the demand for energy of the customers it serves as well as their flexibility to change operation based on market conditions. The population of DSOs does not change over the course of the study.

Weather Forecaster

The weather forecaster does not participate in the markets directly; however, in the DSO+T study, a single weather forecaster is used by the decision-making logic of all participants as they determine the needs and costs for electricity and how to develop their position in the markets. The weather forecaster is described in Section 4.3.1, under General Market Services.

2.1.2 Participant Connectivity Graphs

Transmission System Graph

The transmission system is a simplified, but representative model of the Electricity Reliability Council of Texas (ERCOT). It is composed of 200 substations, graphically modeled as nodes, that are physically interconnected by transmission lines. The system runs as a networked islanded region, but there are no independent islands of operation within it. For simplicity of modeling and accounting, generators operated by generator owner-operators and distribution systems operated by distribution system owner-operators are each assigned to one and only one node in the transmission system.

The capacity limits for lines and operational characteristics and limits for generators (e.g., startup and shutdown costs and times, minimum and maximum power output) are modeled to simulate quasi-steady-state power flow solutions of operation and to be represented in reliability constraints used in the market operations. More details about the transmission system design are provided in Vol. 2, Section 3.0 (Reeve, Singhal, et al. 2022a).

Transaction Graph

The wholesale market participants communicate in a hub-and-spoke configuration with the wholesale market being the hub and the generator owner-operators and DSOs being at the outer end of the spokes. The market timing rules are explained in Section 3.1. No communication bandwidth constraints, delays, or scenarios with communications failures are modeled in the DSO+T study.

Generator owner-operators also need to communicate the characteristics of their generation resources. The wholesale market operator needs to know the type of generation available for operation, including startup and shutdown costs and times, ramp rates, and maximum and minimum generating limits, so it has adequate information to run its algorithms to ensure a reliable mix of generation is operating in real time.

Each participant is modeled as having access to the weather forecaster without any delay or failure scenarios simulated.

2.1.3 Wholesale Marketplace Interfaces to Others

The DSOs represent the electricity customers and their flexibility of operation to the wholesale marketplace. They coordinate with the electricity customers through retail market operations described in the next section. The amount of load secured in the wholesale day-ahead and real-time markets comes from these interactions. The wholesale market cost of supply at the DSO's LMP node is conveyed to its customers based on the wholesale market resolution mechanism with retail price adjustments.

While ERCOT does have asynchronous interfaces and import/export arrangements with other parties in the real system, these external system interfaces are not modeled in the DSO+T study.

2.2 The Retail Marketplace

This section describes the structure of the retail marketplace. It identifies the participants and interfaces between the participants that support the transactive energy coordination mechanism used in the study. This section presents the connectivity graphs for the physical flow of electricity, the communication flow of transactions within the retail marketplace. It also explains the points of interaction with other participants including the wholesale market and bulk electric system. Figure 5 presents a high-level diagram of retail marketplace participants and their interfaces with each other. The wholesale-to-retail interface is also shown but the details of the wholesale marketplace are explained in Section 2.1.

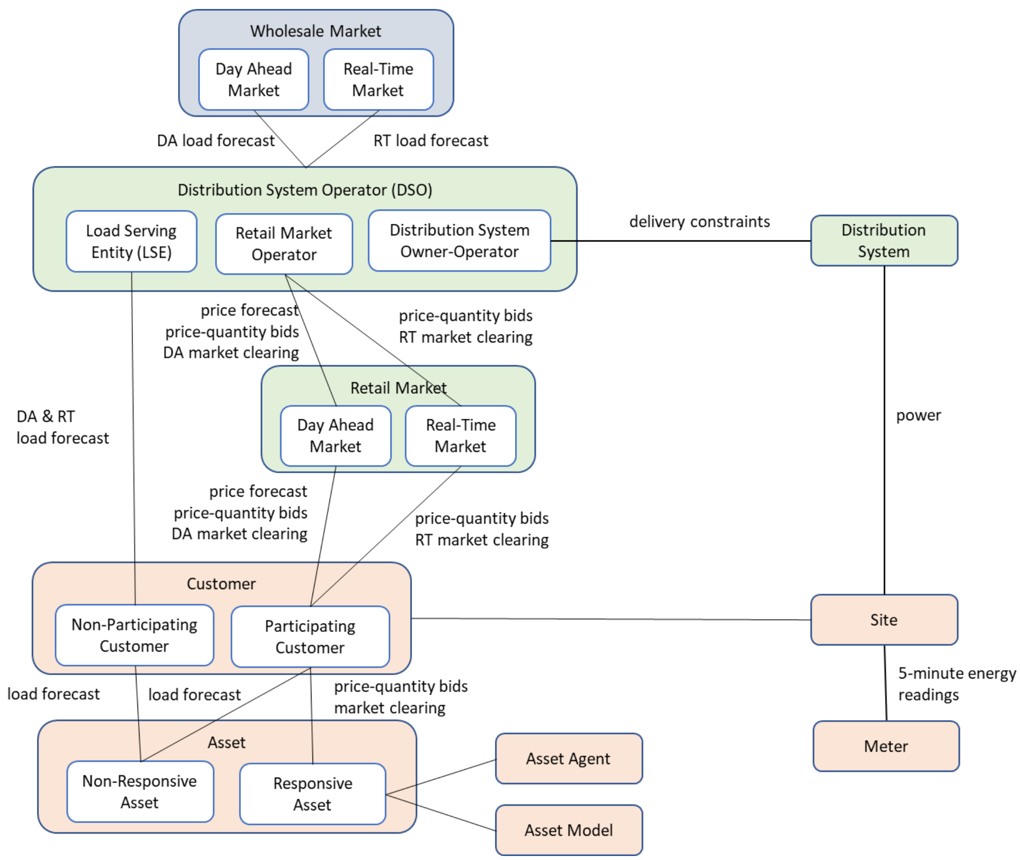


Figure 5. Retail marketplace participants and interfaces.

2.2.1 Types of Participants

The DSO and customers are the primary retail marketplace participants. Each of these entities is responsible for performing specific functions and have oversight for the electrical assets they own and operate as explained below.

2.2.1.1 Customers

There are two types of customers: participating and nonparticipating. Participating customers are registered to participate in the retail market. A participating customer operates one or more responsive assets as well as nonresponsive assets, as explained below. Nonparticipating customers do not participate in the retail market and only have nonresponsive assets.

Assets Operated by Customers

Assets are electrical devices such as HVAC units, water heaters, batteries, and EVs and other electrical loads. There are two types of assets owned and operated by customers. Responsive assets that are dynamically controlled by their customers based on retail market transactive signals. Nonresponsive assets operate independent of the transactive retail market.

Sites

Sites represent the physical positions of customers and their equipment in the electric distribution system. In this study, each customer is assumed to occupy one site and one connection to the distribution system. The flow of energy between the site and the distribution system is measured by a communicating interval meter capable of meeting the performance requirements of the retail marketplace.

2.2.1.2 Distribution System Operator

The DSO is composed of a distribution operator role, a retail market operator role, and an LSE role. The DSO uses LSE and retail market operations components for interacting with the wholesale marketplace and acquiring the LSE's energy needs from the wholesale market. In particular, the DSO combines the aggregated demand from the LSE and the demand cleared from retail market operations to purchase the electricity from the wholesale marketplace.

Load-Serving Entity

An LSE is an intermediatory actor of the DSO that serves retail electric customers through purchases of electricity from the wholesale market made by the DSO. The core activity of an LSE is to aggregate load on behalf of many customers. Based on this information and the information from retail market operations, the DSO makes appropriate arrangements in wholesale markets to meet the forecast load.

In addition to the basic aggregation functions, an LSE establishes rate schedules for all the types of customers, measures customer use, and bills customers. It also plans for load growth and considers potential risks to electricity delivery (e.g., contingencies). In addition to aggregating the loads, forecasting the loads for nonparticipating customers is one of the key functions of the LSE.

Distribution Owner-Operator

The distribution owner-operator is responsible for constructing, operating, and maintaining the physical distribution system. The distribution system consists of hardware that transports electricity between the transmission system and individual retail customers. This entity is responsible for reliable operations of the distribution system, which includes setting capacity limits on equipment and making decisions regarding system upgrades and expansion. The distribution owner-operator relies on the LSE and retail market operator for scheduling the balance of supply and demand.

Retail Market Operator

The retail market operator runs the market according to the transactive energy rules established for the market participants. These rules define the process and information exchange for participating customers to interact with the market. The retail market operator determines the balance of supply and demand at each market cycle and signals the participating customers with the result. The participating customers use the resulting information to plan the control of their responsive assets. To perform this function, the retail market operator collects price-quantity bids from each participating customer and aggregates those price-sensitive bids (see Section 4.2.1.1 for details). Please note that the price-responsive bids from the participating customer are the aggregation of all responsive and nonresponsive assets with that customer.

In addition to the price-quantity bids from participating customers, the retail market operator receives the forecast load of all nonparticipating customers from the LSE. The retail market operator then constructs the price-quantity supply curve based on information from the DSO's interactions with the wholesale market and the capacity limits obtained from the distribution owner-operator. The process by which the retail market operator constructs the supply curve is described in Section 4.2.1.1.

Retail Markets

There are two types of energy markets in the retail marketplace: a day-ahead and a real-time market. The participants in the retail market are the DSO and the participating customers. The retail market operator runs both the day-ahead and real-time retail markets for the DSO. The LSE function of the DSO develops the nonparticipating load forecast for each retail market period (day-ahead and real-time). The participating customers bid their price-quantity curves for each market period. The DSO's retail market operator runs energy markets using the retail supply curve and the aggregated participating customer bids to find the retail electricity price-quantity market clearing.

2.2.2 Membership Qualifications

All participating customers must register with the retail market operator and be qualified to participate in the market. The minimum qualification to participate as a market participant includes:

- The market participants are within the jurisdiction of the given DSO (i.e., electrically connected to the DSO substation) that is running the retail market operations.
- The market participants have at least one responsive asset.
- The market participants agree to the retail rate agreement.

2.2.3 Participant Connectivity Graphs

This section describes the physical and communication connection points among the retail market participants. It also defines the interfaces of the retail marketplace (and its participants) to external parties, including the wholesale market and weather forecaster.

2.2.3.1 Electric Power Distribution System

As illustrated in Figure 6, the electric power distribution system is modeled as radial distribution feeders that receive power from the bulk power system at the transmission substation level.

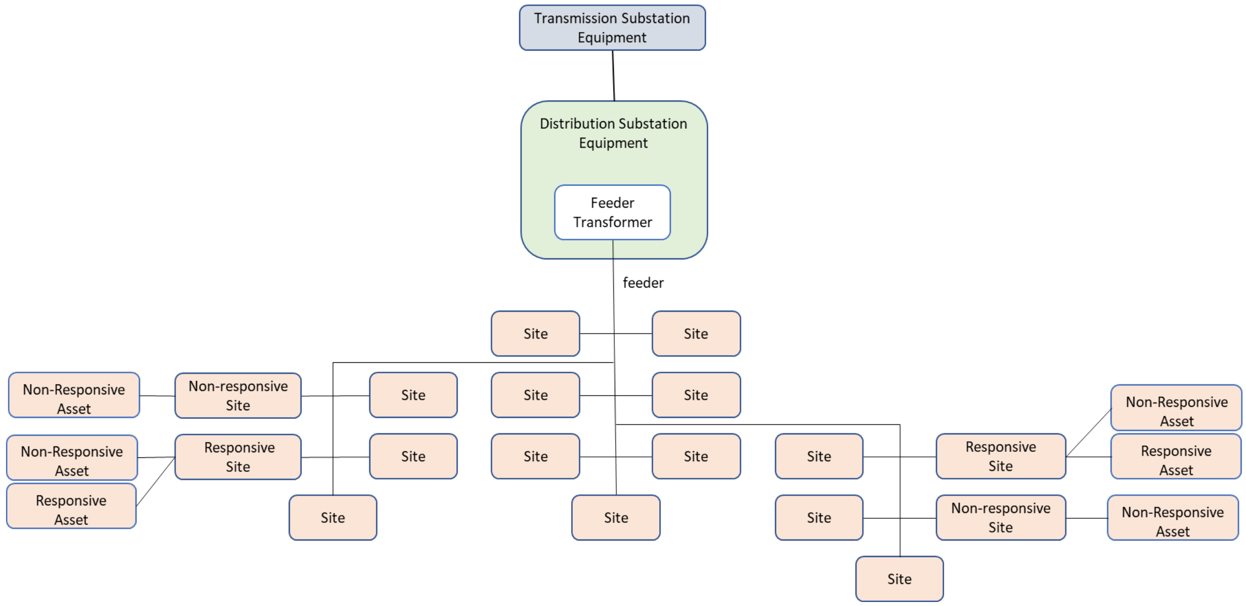


Figure 6. Electric distribution system graph.

In an actual system, there are distribution substation transformers for each phase of a distribution circuit. These transformers reduce the substation voltage to the distribution voltage and, further down each radial phase, service transformers reduce the distribution voltage to the end-use voltage for distribution of electricity to the customers. Each service transformer serves multiple sites, some of which are participating customer sites and some are nonparticipating customer sites. The transport constraints in the distribution system come from the physical limits of the substation equipment and the equipment in the distribution feeders and laterals (e.g., distribution conductor, service transformer).

The DSO+T study simplifies the distribution topology related to retail market operations. Each DSO has only one substation. While a DSO's substation has more than one feeder, a combined capacity limit for all the feeders is used to determine the supply limit for that DSO's retail marketplace. That is, the transport constraint used in the retail market supply curve is simply modeled as the loading limit of a single, three-phase substation transformer that is feeding all distribution circuits for that DSO.

Also recall that each DSO is connected to the transmission system in one location through one step-down transmission transformer. From a retail marketplace perspective, this means that each DSO will have only one locational wholesale price from each day-ahead and real-time market clearing.

These simplifying physical distribution system modeling assumptions enable the DSO's retail market operator to run one day-ahead and one real-time series of markets and manage physical transport capacity limits to its customers. In an actual system, a DSO could have multiple connection points to the transmission network. Each distribution substation fed by a different transmission node would operate with the locational wholesale price for that node and with the physical transport capacity limits for the substation. In this case, a retail marketplace would be set up for each distribution substation to operate the transactive retail day-ahead and real-time markets. The customers connected through that distribution substation would participate in that local retail marketplace and the DSO's retail market operator would manage multiple retail marketplaces.

2.2.3.2 Transaction Graph

This subsection presents the logical communication connectivity among the retail market participants. Figure 7 illustrates the channels of communication between market participants. Starting with the information to run the retail market, the day-ahead retail market receives the price forecast for the next 48 hours from the retail market operator at the start of a market cycle. The retail market operator also contributes the price-quantity supply curve to the retail day-ahead market. The participating customers use the price forecast for the day-ahead market to develop their price-quantity bids and submit them to the retail day-ahead market. At the close of the market cycle, the day-ahead market broadcasts the clearing prices and quantities for the next 48 hours to the participating customers and the retail market operator.

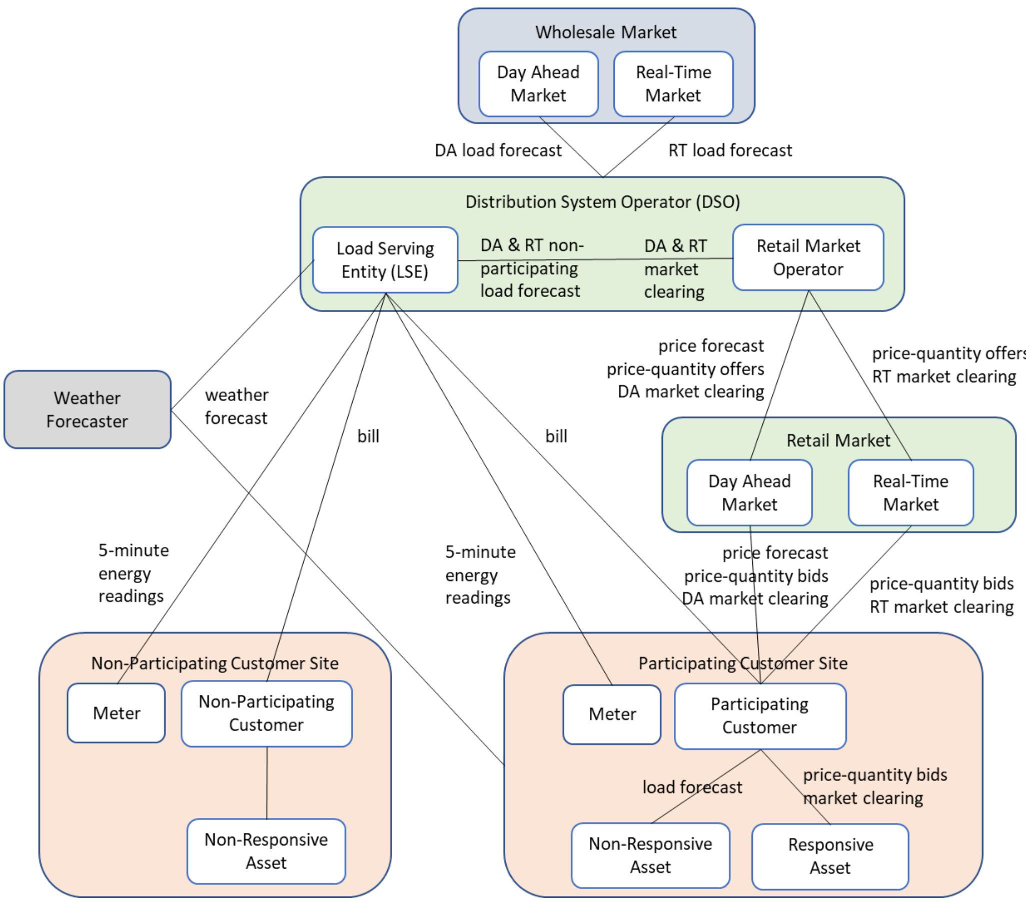


Figure 7. Transaction graph for marketplace communications.

The same process is done for the retail real-time market except there is no real-time price forecast information. Instead, the most recent day-ahead market clearing is used by the participating customers to develop their price-quantity bids. Participating customers also use the real-time prices cleared from previous cycles in developing their price-quantity bids.

Turning to the participating customer site box in the Figure 7, participating customers communicate the day-ahead price forecast to their responsive assets, who each develop a price-quantity curve that the participating customer aggregates along with a forecast of load from their nonresponsive assets. Similarly, the responsive assets develop price-quantity curves for the real-time market but use the latest day-ahead market clearing as their forecast. Every time the day-ahead or real-time markets clear, the result is communicated to the responsive assets.

The LSE receives meter energy-use readings on a 5-minute basis from both participating and nonparticipating customer sites. The LSE uses that consumption information to calculate the monthly bill according to each customer's respective tariff and sends to each customer. To calculate a participating customer bill, the LSE receives the day-ahead or real-time market clearing information from the retail market operator. The tariff structures for both participating and nonparticipating customers are detailed in Vol. 4, Section 4.1 (Pratt, et al. 2022). It also calculates the nonparticipating customer load forecasts used by the retail day-ahead and real-time markets and sends that information to the retail market operator. The nonparticipating customer load forecast is also used by the wholesale market bidding function of the DSO, who combines it with the results of the retail day-ahead and real-time markets to develop day-ahead and real-time load forecasts for the wholesale market.

2.2.4 Retail Marketplace Interfaces to Other Entities

This section describes the interface of the retail market participants to others who are not direct participants. As illustrated in Figure 7, the entities that interface outside of the retail marketplace are the wholesale market and the weather forecaster.

The wholesale day-ahead market bidding function of the DSO uses the nonparticipating customer load forecast from the LSE and combines it with the results of the retail day-ahead market to develop load forecasts to submit to the wholesale day-ahead market. Once a day, the DSO receives wholesale market clearings (cleared prices and quantities) from the wholesale day-ahead market.

The wholesale real-time market bidding function of the DSO works in an analogous fashion using the load forecast from the LSE combined with the results of the retail real-time market to develop load forecasts to submit to the wholesale real-time market every 5 minutes.

The DSO+T study uses a general weather forecasting service to provide weather information to the participating customers and LSE. The LSE and participating customers subscribe to the ambient temperature and solar irradiance level at their corresponding locations from the weather forecaster. The LSE and participating customers use the weather information to forecast nonresponsive assets load quantities for each day-ahead and real-time market cycle. No information goes to the weather forecaster from the LSE and participating customers.

In an actual system, weather forecasting services can be provided by many third-party organizations who are independent of the marketplace. Connections with other outside parties may exist in different situations (such as fuel vendors for combined heat and power units), but these are not modeled in the DSO+T study.

3 Marketplace Design

This section defines the interfaces for interaction between the marketplace participants. It provides details on the items that are traded or negotiated for coordination: a) day-ahead operational price/quantity schedules and b) a real-time operational price/quantity. It also presents the design for coordination of the day-ahead and real-time markets in the wholesale and retail marketplace, and lastly the functions the DSO must do to coordinate between the wholesale and retail marketplaces.

3.1 Wholesale Market Design

The wholesale market is designed to fulfill the ISO's objective to ensure reliable operation of the system and seek operational efficiency of the wholesale market under constraints imposed for reliability. The design uses a two-settlement process consisting of day-ahead and real-time markets. When determining wholesale market prices, all wholesale energy trading is assumed to be done through the market process. While the valuation process does consider bilateral trades (Pratt, et al. 2022, Section 3.3.1), the modeling of such bilateral agreements in simulation and market design was determined to be more complex and prone to be less realistic than presuming the generator owner-operators and DSOs were representing all their respective generation and demand through the economic constructs of the wholesale day-ahead and real-time markets.

3.1.1 Wholesale Day-ahead Market Participant Interface

The wholesale day-ahead market sets up the schedule of operation of the generators and the DSOs for the coming day. Through the positions taken prior to day-ahead scheduling, the ISO sees that reliability constraints are honored, while allowing a competitive market to seek a balance of bulk system generation and DSO-managed demand. For the DSO+T study the participants are assumed to be registered and qualified to participate in the market. See a summary of equations and definitions in (Li and Tesfatsion 2009; Tesfatsion and Battual 2020).

Generator Owner-Operator

Generation owner-operators communicate the following information to the market operator for each hour of the coming day by 10 a.m.

- Marginal production cost function of each generator, i.e., a piecewise linear segmented curve of minimum marginal cost it is willing to accept at each real power output point, including production cost coefficients ($/hour, $/MWh, MW)
- Dispatchable capacity constraints for each generator, i.e., lower and upper limits (MW)
- Ramp constraints for startup, normal up, normal down, and shutdown conditions (MW/min)
- Minimum up-time/down-time constraints (hours)
- Cold-start cost ($)
- Cold-start time (hours)
- Hot-start cost ($)
- Shutdown cost ($)

DSO

The DSOs submit bids to the wholesale market operator for each hour of the next day's 24-hour wholesale day-ahead market. The AMES market simulation software model accepts a fixed (i.e., non-sensitive to price) load value component and a price-sensitive demand schedule component. While the DSO+T project's coordination framework is designed to use a DSO-supplied price-sensitive demand schedule, simulation issues associated with getting the basic wholesale market process to run smoothly throughout the yearly variations of operating conditions led to simply simulating a fixed-load bid for each hour by the DSOs (please see Section 5.3 for a description of future work in this area). Nevertheless, as explained in the retail marketplace sections, these wholesale day-ahead market fixed-load bids have a nonparticipating (price insensitive) customer component and a participating (price-sensitive) component that is based on a price provided to the customers from an LMP forecaster (see Section 4.3.2).

Reliability Coordinator

The reliability coordinator sets the following information for system-wide and zonal reserves.

- System-wide up and down power reserve requirements (MW for each market period)
- Zonal up and down power requirements for each zone (MW for each market period)

The reliability coordinator also gets information from the transmission owner-operator to model the transmission system for reliability analysis and market calculations. This includes the parameters to model the transformers and transmission lines, their capacity limits, network topology, and nominal voltage levels.

3.1.2 Wholesale Day-ahead Marketplace Resolution Process

The wholesale market operator collects all demand bids from the DSOs and supply offers from the generator owner-operators. Given the network and generator modeling information, the wholesale market operator resolves the market while observing operational constraints. Operational constraints are enforced using a SCUC optimization algorithm and a SCED algorithm. The unit commitment ensures enough controllable generation resources are operational each hour and the economic dispatch sees that generation is dispatched to withstand operational contingency scenarios (such as line or generation outages).

The wholesale market operator computes hourly LMPs and power commitments for the day-ahead market by solving bid-/offer-based direct current optimal power flow problems that approximate the more accurate alternating current optimal power flow problems. These computations are accomplished with repeated calls to the optimal power flow algorithm.

When there are no transmission line constraints violated, the result is uniform LMPs across the system. When energy transport is constrained the result is differentiated LMPs so that DSOs will see differentiated prices at the transmission substation delivery point. As a DSO has only one delivery point, it will only see one LMP for each market period. Differentiated prices will engage the flexibility in DSOs to consume more or less to help relieve transmission congestion constraints. The hourly LMPs are then communicated back to the generator owner-operators and DSOs and used to prepare for the wholesale real-time market and operations.

In the case of algorithmic nonconvergence on a particular day-ahead 24-hour period, the simulation uses the resulting values from the previous day's market. For example, if the upcoming day-ahead market for 15 May did not converge to a price, the prices from the 14 May market are used.

3.1.3 Wholesale Real-time Market Participant Interface

The wholesale real-time market sets up the schedule of operation of the generators and the DSOs for the next 5-minute operating period. The ISO uses the results of the real-time market as the desired operating positions of the generators and DSOs to analyze the reliable operation of the system given the generating units available for dispatch in the next 5-minute period. (The market simulator simultaneously solves a 6-interval lookahead window (30-minute window) for deriving the next 5 minutes of operation.)

The generator owner-operators have already communicated the operating characteristics of their generators in the wholesale day-ahead market. They have also taken a committed position for the real-time hour of operation based on the results of the day-ahead market. Based on changing operating conditions, the generation owner-operators update information for the wholesale real-time market for the next 5-minute period. These reflect corrections to the positions taken in the wholesale day-ahead market. The information includes the marginal production cost function of each generator, which is a piecewise linear segmented curve of minimum payment the generator is willing to accept at each real power output point, including production cost coefficients ($/hour, $/MWh, MW).

Similarly, the DSOs submit bids to the wholesale market operator for the next 5-minute real-time market period based on corrections to the positions they have already taken in the wholesale day-ahead market. As with the wholesale day-ahead market, the bids include a fixed (non-sensitive to price) load value component and a price-sensitive demand schedule component. For the DSO+T study, the price-sensitive demand was derived based on a forecasted LMP and represented as a fixed demand. A future improvement would be to represent this portion of the DSO demand as a price-quantity bid curve.

The reliability coordinator updates the following information for system-wide and zonal reserves.

- System-wide up and down power reserve requirements (MW for each market period)
- Zonal up and down power requirements for each zone (MW for each market period)

The reliability coordinator also gets information from the transmission owner-operator to model the transmission system for reliability analysis and market calculations. This includes any changes (such as outages or return to service) to update the model of the transmission network.

3.1.4 Wholesale Real-time Marketplace Resolution Process

For every 5-minute real-time market period, the wholesale market operator collects all demand bids from the DSOs and supply offers from the generator owner-operators. Given the network and generator modeling information, the market operator resolves the market while observing operational constraints. Operational constraints are enforced using the SCED algorithm to see that generation is dispatched to withstand operational contingency scenarios (such as line or generation outages).

The wholesale market operator computes real-time LMPs by solving the direct current optimal power flow problem. The 5-minute LMPs are then communicated back to the generator owner-operators and DSOs and used to prepare for the wholesale real-time market and operations. Differentiated prices engage the real-time flexibility in DSOs to consume more or less to help relieve transmission congestion constraints.

In the case of algorithmic nonconvergence on a particular 5-minute period, the simulation uses the resulting value from the previous 5-minute real-time market. For example, if the upcoming real-time market for 11:15 a.m. did not converge to a price, the price from the last real-time market for 11:10 a.m. is used.

3.1.5 Relationships of Wholesale Day-ahead and Real-time Exchanges

The daily and hourly timelines for the wholesale day-ahead and real-time markets are depicted in Figure 8 as augmented from (Tesfatsion and Battual 2020). The day-ahead market requires a significant lookahead horizon to mimic what we see in typical wholesale markets today. The real-time market is interleaved with the day-ahead market process making corrections on the corresponding day-ahead operational hourly commitments. The way the wholesale market participants develop their day-ahead and real-time market bids is explained in Section 4.1.

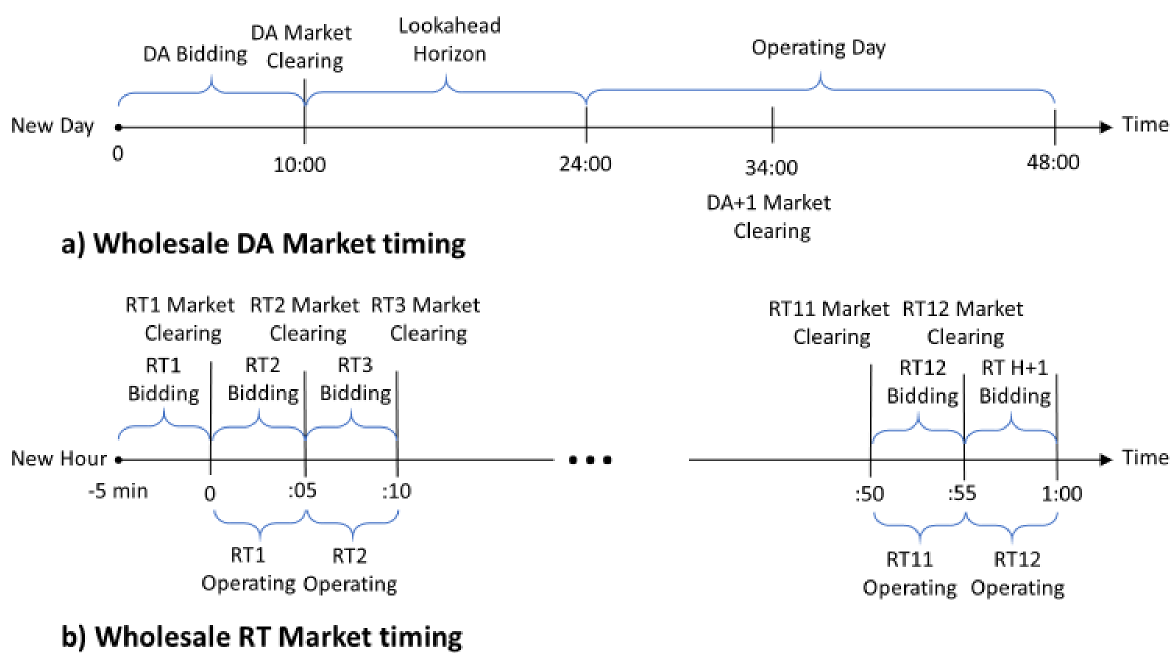


Figure 8. Wholesale timing diagram a) day-ahead and b) real-time markets.

3.2 Retail Market Design

The retail market provides a market-based control and coordination platform for participants through day-ahead and real-time energy markets. For both markets, participating customers prepare their scheduled energy bids in terms of their responsiveness to changes in price. While preparing their bid curves, they consider their cost saving and amenity/comfort. Similarly, the DSO submits its supply price-quantity curve to the retail market operator. While preparing the supply bid curve, the DSO factors in the physical limits of its infrastructure (e.g., substation limits to transport energy), the wholesale cost of energy from the wholesale day-ahead and real-time markets, and the forecast wholesale electricity price.

Figure 9 shows the process flow for the retail day-ahead market. The following sections describe these steps in greater detail.

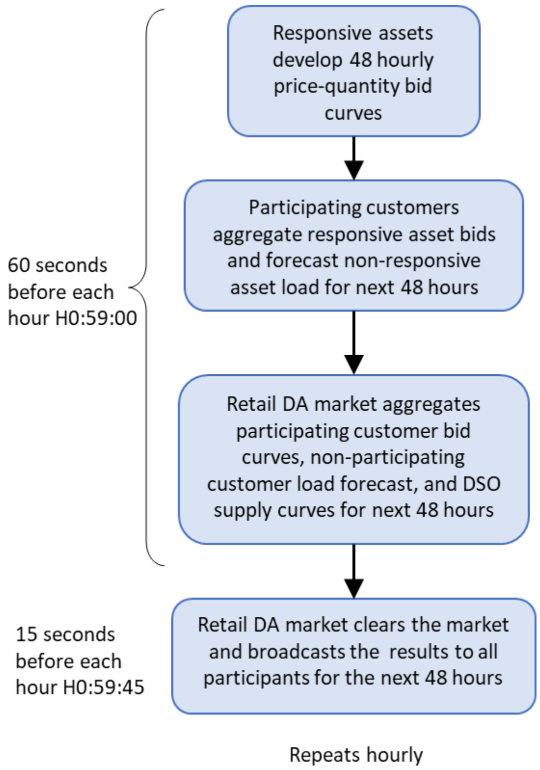


Figure 9. Process flow of the retail day-ahead market.

3.2.1 Retail Day-ahead Market Participant Interface

The retail day-ahead market is designed to support the DSO's decision-making for participation in the daily 24-hour wholesale day-ahead market. As explained in the discussion on the wholesale day-ahead market in Section 3.1.1, the DSO must submit information to the wholesale day-ahead market by 10 a.m. every day. In the DSO+T study, the retail day-ahead market is designed to run every hour with a lookahead horizon of 48 hours. The hourly run of the retail day-ahead market provides a refinement mechanism for participating customers to improve their price-quantity bids as time proceeds and new information from the operating conditions of assets, weather, and price forecasts is received. At the start of each retail day-head hour market period, the market receives the forecast price for the next 48 hours from the retail market operator. Each retail market operator has a price forecaster for the wholesale LMP at the transmission node where the DSO corresponding to the given retail market operator is physically connected. More details on the LMP price forecaster are provided in Section 4.3.2.

A diagram of the sliding-window, hourly retail day-ahead market operation is illustrated in Figure 10. Every row represents one hourly run of the retail market that clears the price-quantity for the DSO's distribution feeder the next 48 hours starting from that market hour. For instance, the blue cells represent the prediction for the next hour of actual operation with the cells to the right of that representing predictions for the other 47 hours into the future. Similarly, every column represents a time series of cleared quantities for the given hour in the past day-ahead market operation intervals. This means that by the time participating customer assets are implementing their actual flexibility strategy, the market for that hour has been cleared 48 times. This ensures a converged desired operating plan and stable operation of the transactive agents as they enter real-time operation.

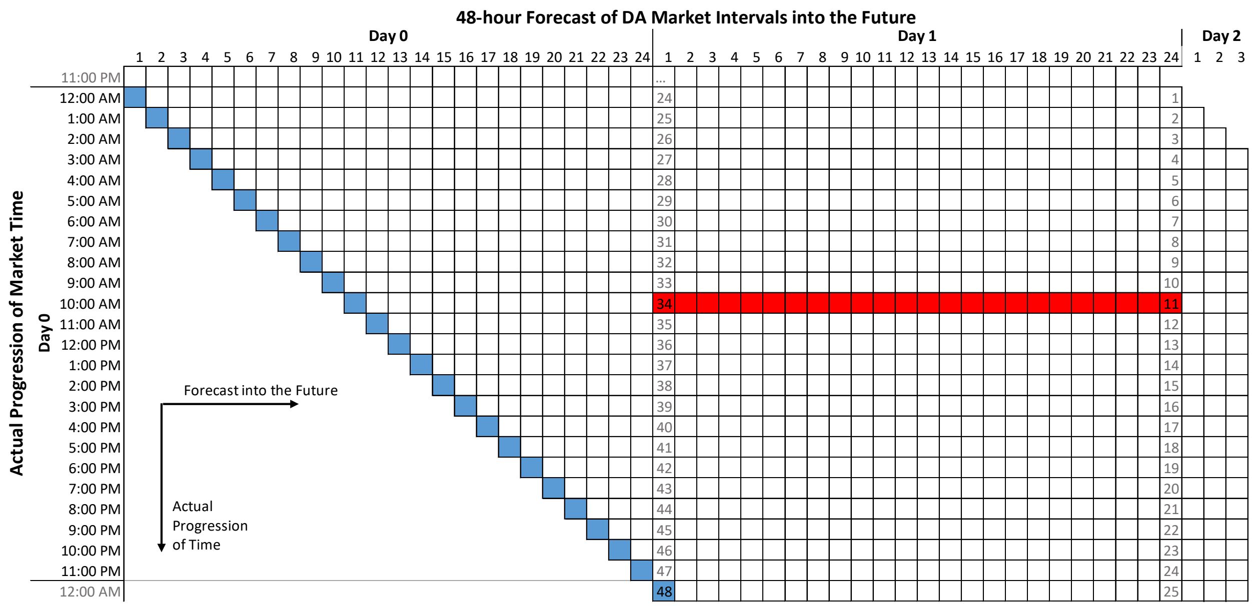


Figure 10. 48-hour, sliding-window, retail day-ahead market progression.

The DSO aggregates the retail day-ahead price-responsive bids from the participating customers with the forecast loads of the nonparticipating customers to form a single aggregated demand bid. A pseudo-wholesale market clearing is performed using the retail market operator's LMP forecaster to obtain the load demand the DSO submits once a day to the wholesale day-ahead market at the time represented by the row with red boxes in Figure 10. The vertical numbers in the cells represent the number of times the hourly market has been cleared prior to the submission of the wholesale day-ahead bid. This shows that the first hour of the bid has had 34 iterations, while the last hour has had 11. The process of converting the retail aggregated demand bid into a single-point demand bid to the day-ahead wholesale market is presented in Section 4.1.2. When the actual time of finalizing the plan arrives (10 a.m. the day before), the best estimate of the responsive assets' price-quantity curves is available for the DSO's interaction with the wholesale day-ahead market.

The progression of the 48-hour lookahead window provides market iterations where participants are able to react to the market clearing information from previous iterations and incorporate new weather and asset operation planning information that helps participants converge to a stable, optimal-seeking operating plan as they enter real-time operation. Note, the participating customers' bills are calculated based on their cleared day-ahead price-quantity bids that correspond to the 24 red boxes in Figure 10. The bills are then augmented by the results of the retail real-time market and their actual performance.

3.2.1.1 Negotiation Process

All participants must register to the retail market operator and be qualified to participate in the market. In the DSO+T study, the participants are populated according to the demographic targets for the various case studies. The following describes the interactions of the market participants to negotiate with the retail day-ahead market.

The negotiation process defines the rules for market participant information exchange that results in a market solution (i.e., a market clearing). The negotiation process focuses on rules for collecting the demand bids from the buyers and supply bids from the producers. This information is processed by the retail day-ahead market to clear the market. The results are then communicated back to the participants. The following paragraphs describe the negotiation process among the retail day-ahead market participants:

In preparation for the negotiation process, each responsive asset prepares a set of bid curves to participate in the retail day-ahead market. Since the market is an hourly market that runs for the next 48 hours, each responsive asset prepares 48 bid curves at each market interval. Each responsive asset prepares its bid using the structure as illustrated in Figure 11. Each responsive asset bid curve is defined by four points:

(Q_{min}, P_{max}), $(Q_{des}, P_{des}+ d_b/2)$, $(Q_{des}, P_{des}- d_b/2)$, (Q_{max}, P_{min}).

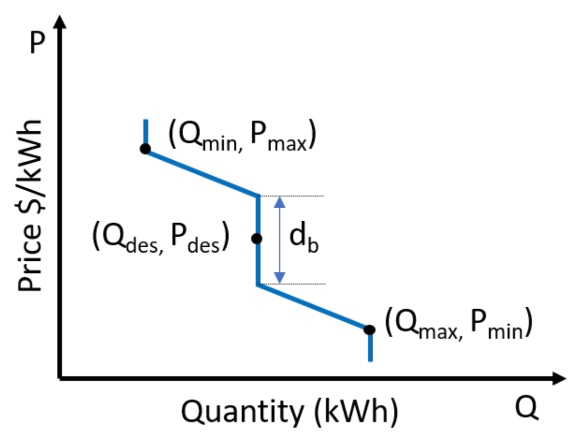


Figure 11. Responsive asset bidding information.

Each point on the price-quantity bid curve is represented for each hour h, where h goes from 1 to 48 and where:

$P_{\max}$ ($/kWh): Maximum energy price for forecast hour h

$P_{\min}$ ($/kWh): Minimum energy price for forecast hour h

P_{des} ($/kWh): Energy price anticipated for desired optimal quantity to be used in forecast hour h

$Q_{\min}$ (kWh): Lowest quantity of energy the asset needs to consume for hour h

$Q_{\max}$ (kWh): Highest quantity of energy the asset could consume for hour h

Q_{des} (kWh): Desired quantity at hour h

d_b ($/kWh): Price deadband within which the asset does not change the quantity of energy to use for hour h

The length of the price deadband depicted in the figure is exaggerated in proportion to the quantity range for illustrative purposes. In reality, the deadband is small.

The core concept behind the flexible bidding mechanism is that the participating customer is willing to consume less energy when the price is higher and more when the price is lower. A small price deadband is introduced in the bid curve so that the asset remains at the desired energy quantity of consumption or production if market price changes insignificant. This prevents issues like hunting and over reaction to small market changes. It can also help reduce the physical costs assets incur in changing their response such as the wear and tear from needless control operations. The price deadband brings stability benefits to retail market operations by discouraging small changes in their position if market prices are quiescent.

Figure 12 shows the transaction exchange mechanism of the retail day-ahead market. For a single market interval, the retail market operator collects a set of 48 bid curves from each participating customer and informs them about the cleared transactive market marginal energy prices ($/kWh) for each of the corresponding 48 hours. The transactive exchange process is described below for a single market interval. The market operates hourly at 1-minute before the top of the hour.

Step 1. Each participating customer collects the prepared bids from the responsive assets at its site and forecasts the demand of the nonresponsive assets. The participating customer then aggregates the bids from all responsive assets (in the form described above) and the aggregated forecast demand quantity from the nonresponsive assets to form a single price-quantity bid curve that it submits to the retail day-ahead market. At every market interval, the participating customer submits 48 bid curves for the next 48-hour interval.

Step 2. The retail market collects and aggregates bids from all participating customers and the forecast load of nonparticipating customers (see Section 3.2.2). It also receives a supply price-quantity curve from the DSO for each of the 48 hours.

Step 3. The retail market operator uses the submitted information to clear each of the 48 hours in the current retail day-ahead market interval.

Step 4. The cleared retail marginal prices ($/kWh) for the next 48 hours are communicated to the participating customers and DSO.

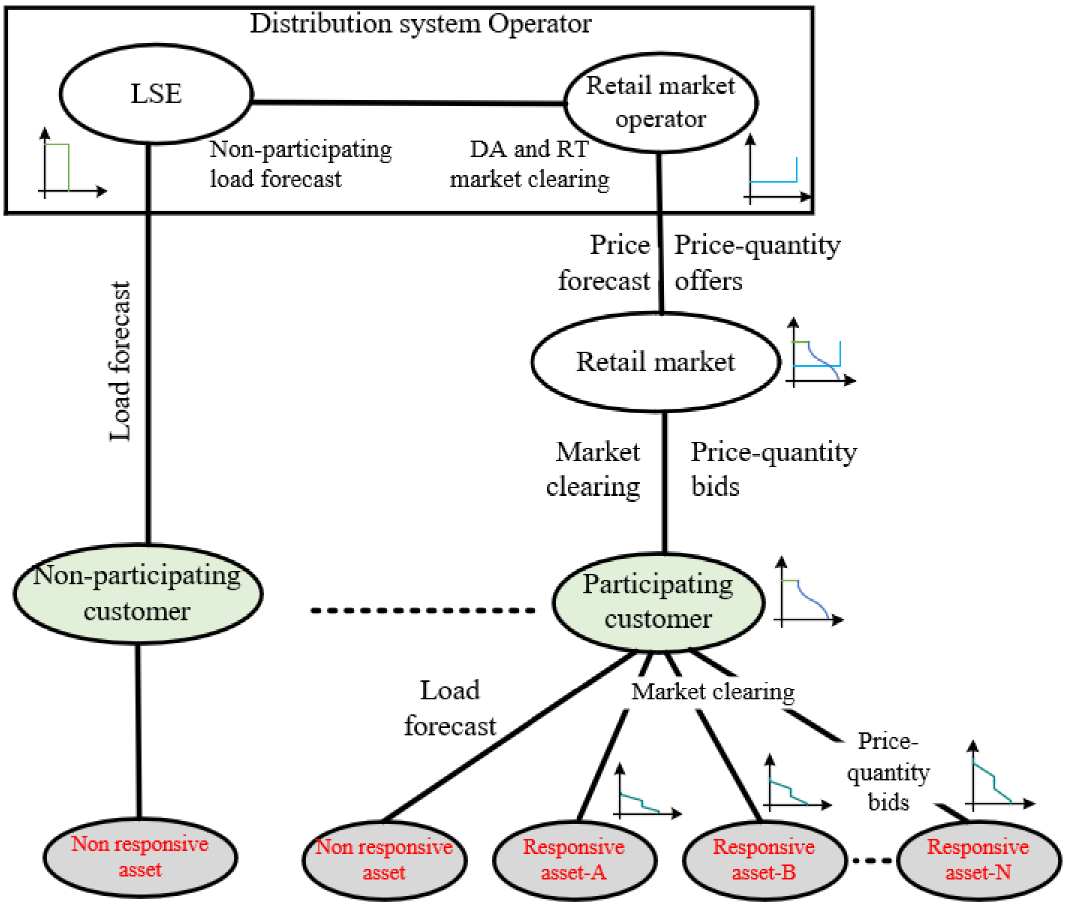


Figure 12. Retail day-ahead market transactive exchange process.

3.2.1.2 Operating Process

The participating customer, who aggregated the bid curves from the responsive and unresponsive assets, shares the cleared retail day-ahead market marginal prices for the 48 hours to each responsive asset. Only the price quantities cleared for the wholesale operating hours are binding and the rest of the hourly prices are used by the responsive assets to prepare their updated day-ahead bids for the next hour so they are better prepared for real-time operation.

3.2.1.3 Measurement and Verification

The retail market operator records the quantity cleared for the 24 hours in the retail day-ahead market that corresponds to the wholesale market clearing for each participating customer along with the cleared marginal price of energy for each of the wholesale day-ahead market hours. In the DSO+T study, this information is passed to the LSE for billing.

In a real-world situation, the retail day-ahead market may also perform the following actions:

1. Continuously monitor the operations of participating customers and record values at each market interval

2. Continuously monitor performance of all participating customers with respect to bid and market-cleared quantity to identify any behaviors outside of market rules
3. Record and maintain past performance of participating customers
4. Request additional information and measurements from market participants (if needed) as a verification process.

The DSO may use this information to better represent the performance of its customers as it interacts in the wholesale marketplace. In addition, the rate policy on the retail day-ahead price-quantity bids' financial commitments could be designed to incentivize participating customers with updated information the DSO may obtain in addition to the wholesale day-ahead market clearing. For example, each retail market iteration could result in a price-quantity commitment that can be refined as the market progresses every hour with new information such as weather forecast changes and equipment outages.

3.2.1.4 Settlement and Reconciliation

The LSE receives the results of the retail day-ahead market clearing and uses the price-quantity pair for the hours corresponding to the wholesale market bids as input to calculating the bill for each participating customer. The day-ahead component of the bill is adjusted based on the actual quantity consumed or supplied and the difference in quantity over the operating hour is reconciled at the cleared price from the retail real-time market. The settlement is done after the corresponding hourly wholesale day-ahead market interval has elapsed.

3.2.2 Retail Day-ahead Marketplace Resolution Process

As a part of the negotiation step of Section 3.2.1, the retail market operator collects sets of day-ahead price-quantity bid curves from each participating customer and aggregates them into a set of 48 bid curves that represent the price-responsiveness of the DSO's customers. In addition to the price-quantity bids from participating customers, the retail market operator receives the set of forecast loads of all nonparticipating customers from the LSE for the next 48 hours.

The retail market operator constructs the day-ahead supply curve for each hour using information provided by the DSO. The retail day-ahead market uses a double-auction clearing mechanism to find where the incremental bid for demand equals the incremental offer for supply. The process of forming the supply curve and the retail market clearing is explained in detail in Section 4.2.1.

3.2.3 Retail Real-time Market Participant Interface

The retail real-time market is designed to encourage participating customers and their assets to respond to real-time operating conditions as reflected in the prices coming from the wholesale market and any changes to local congestion issues on the distribution circuit. The retail market participants have a similar interface to the market as the retail day-ahead market. The main difference is that price-quantity curves are developed for the next retail real-time market 5-minute period.

Figure 13 describes the process flow for setting up and resolving the retail real-time market. The details of the information exchange and their contributions to the process are described in the following sections.

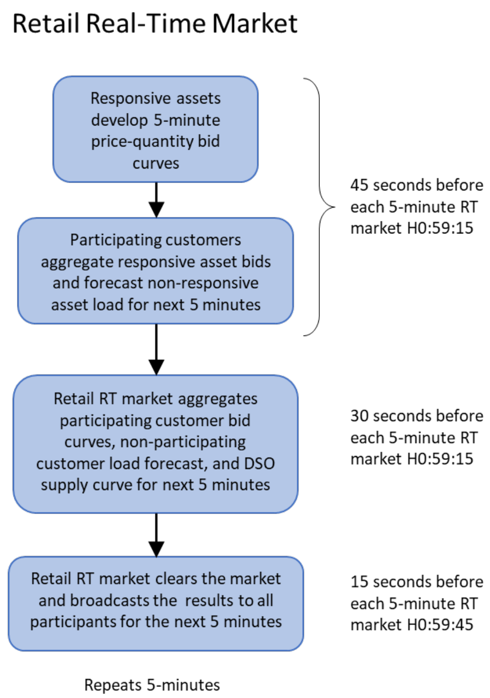


Figure 13. Process flow of the retail real-time market.

The negotiation process for the retail market is performed for one 5-minute market interval. Each responsive asset prepares a real-time demand bid for the next 5-minute interval. The real-time bid is prepared using the same structure as for the retail day-ahead market illustrated in Figure 11. The detailed process of how the real-time bids are constructed is discussed in Section 4.2.2.1.

At every retail market interval, each participating customer: a) collects bids from the responsive assets at its site; b) forecasts demand of the nonresponsive assets from the hourly forecast performed during the given day-ahead market interval; and c) aggregates the bids from all responsive assets and the forecast demand quantity from the nonresponsive assets to form a single price-quantity bid that it submits to the next retail real-time market. The market collects and aggregates bids from all participating customers and the forecast load of nonparticipating customers as was done for the retail day-ahead market (see Section 3.2.2). It also receives a supply price-quantity curve from the DSO for the next 5-minute market period. The retail market operator uses the submitted demand curves and supply curve to clear the market for the next 5-minute period. The cleared real-time prices ($/kWh) for the next 5 minutes are then communicated to each participating customer and DSO.

The participating customer shares the cleared marginal prices for the next 5-minute real-time market period to each responsive asset. The participating asset then responds to the cleared price and its state of operation, which can change during the retail real-time negotiation process.

The LSE receives the results of the market clearing and uses the metered consumption of the responsive assets for calculating the bill for each participating customer. The difference between the retail day-ahead cleared quantity and the metered consumption is billed at the cleared retail real-time price.

3.2.4 Retail Real-time Marketplace Resolution Process

Like the retail day-ahead market, the retail real-time market also uses a double-auction clearing mechanism to find where the incremental bid for demand equals the incremental offer for supply. The process of the market clearing is explained in detail in Section 4.2.1.1.

For a single market period, the retail market operator collects a bid curve from each participating customer and informs them about the cleared marginal energy prices ($/kWh) for the next market interval. The retail real-time market operates every 5 minutes at 30 seconds prior to the top of the next 5-minute market period. The transactive negotiation process for a single market period is similar to that of the retail day-ahead negotiation process (described in Section 3.2.1.1).

3.2.5 Relationships of Retail Day-ahead and Real-time Exchanges

As discussed in Sections 0 and 3.2.3, the retail day-ahead and real-time markets have different timing of operations. The day-ahead market is an hourly market with a 48-hour lookahead horizon while the real-time market is a 5-minute market that runs for the next 5 minutes of operations.

The real-time market acts as a correction market from the planned hourly operation obtained through the day-ahead process. The market position (price for the hourly quantity of energy) from the day-ahead market is known before the real-time market bidding period opens. This information is used as a reference operating point (a desired plan of operation) during the real-time market operations in Figure 11. Since the day-ahead market clears a price-quantity for each hour and the real-time market clears every 5 minutes, a participating customer adjusts the day-ahead plan for that hour into 12 5-minute real-time market intervals. The way this is done is up to the participating customers and their responsive assets; however, the approach needs to consider the transition from one hour to the next. The DSO+T study applies a smoothing algorithm so that the desired quantity consumed between the last 5-minute period in the previous hour has a smooth transition to the first 5-minute period of the following hour. Omitting this smoothing can result in large spikes or drops in demand at the start of each hour due to the unintended synchronization of assets. This is explained in Section 4.2.2.1.

The participating customers develop their price-quantity curve for each real-time retail 5-minute period and submit these curves to the market. The retail market operator receives the result of the wholesale 5-minute market from the DSO and develops the supply curve for the retail market. The market then has all the information needed to clear the market and communicate the results to the participants.

Figure 14 illustrates the timing of interactions between the retail day-ahead and real-time markets. Consider hours, minutes, and seconds of time as HH:MM:SS. In the day-ahead market process, 1 minute before the start of the market hour H1 (i.e., H0:59:00) each participating customer collects the price-quantity bids from its responsive assets and forecasts the demand of the nonresponsive assets. The market aggregates the responsive bids and the forecasted nonparticipating customer load from the LSE to run the retail day-ahead market for the next 48 hours. At H0:59:15, 45 seconds before the start of the next operating hour, the market broadcasts the cleared price quantities for the next 48 operating hours to all participants. The responsive assets use that day-ahead cleared prices as a reference for preparing their real-time bids as depicted in the Figure 14 and explained above.

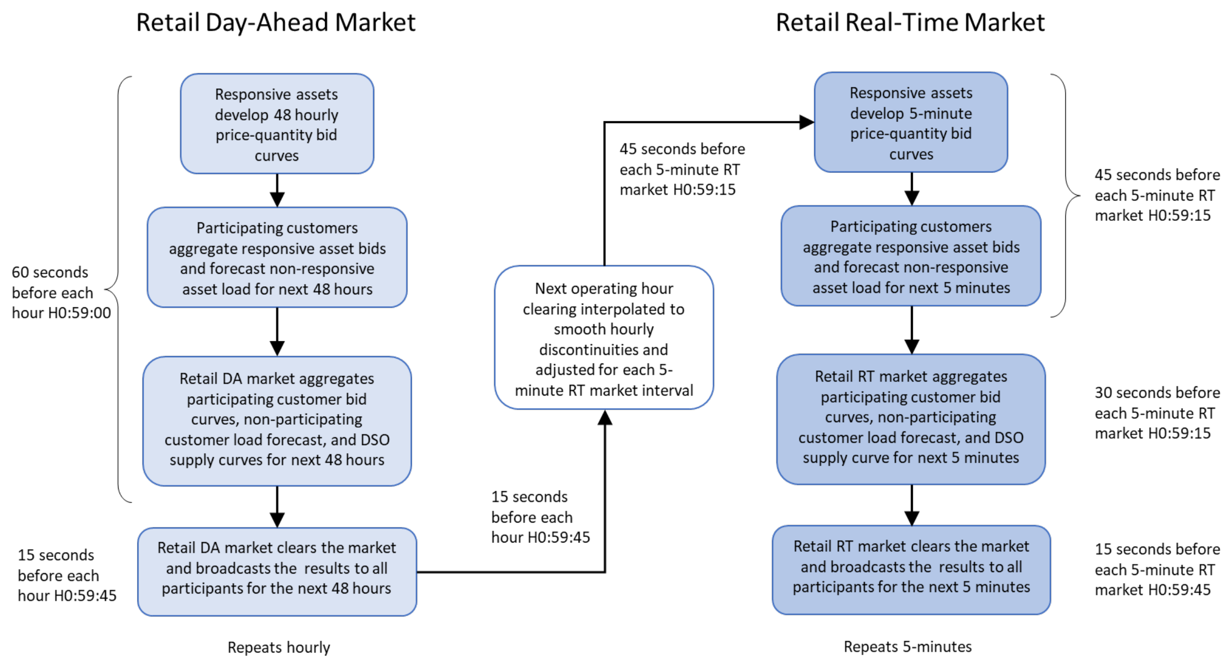


Figure 14. Retail day-ahead and real-time markets coordination.

The first retail real-time market interval for H1 uses these bids and runs 30 seconds prior to the operation of the market interval (i.e., H0:59:30) and sends the cleared price back to the market participants 15 seconds prior to the close of the 5-minute interval (i.e., H0:59:45). The responsive assets have 15 seconds from the receipt of the market signals to translate the real-time market clearing price to the operational control signals for the responsive assets. The second market interval for H1 uses the bids for the next 5-minute interval and runs at H1:04:30. The cleared price is sent back 15 seconds prior to the close of the second 5-minute market at H1:04:45. The market continues this progression in 5-minute increments over the hour.

4 Marketplace Participants Decision Making

Each participant in the wholesale and retail markets executes a decision-making process for interacting with the other participants in the marketplace. This section explains the logic used in the participants' decisions.

4.1 Wholesale Marketplace Participants

The wholesale marketplace seeks equilibrium between the generator owner-operators and the DSOs who serve their electricity customers.

4.1.1 Wholesale Generator Participant

As described in Section 3.1.1, the AMES wholesale market simulator configured for the DSO+T study assumes that the generator accurately reflects their marginal cost of production and generation operating characteristics (such as minimum compliant loads, ramp rates, and startup costs) to the wholesale market operator. The information is cost based. There is no competitive strategy for bidding modeled in the simulation.

The generator models consider an assumed cost of fuel (if any) and the heat-rate characteristics of a steam-generating unit, along with variable operations and maintenance costs. More details on these assumptions are provided in (Reeve, Singhal, et al. 2022a, Section 2.2.1). These are used to create the price-quantity supply curves along with minimum and maximum operating ranges.

Forecasts, such as weather, loads (from DSOs), and LMPs are taken into account through the wholesale day-ahead market process, which also resolves the reliability constraints through the SCUC and SCED process. This results in the generator day-ahead operating positions.

4.1.2 Wholesale DSO Participant

The DSO is designed to be a nonprofit entity who represents the load (including any portion that is price sensitive) in its jurisdiction as accurately as possible to the wholesale marketplace. It also represents to its customers the wholesale cost of energy as accurately as possible. The customer tariffs are designed to cover the costs of operating the DSO and are collected by the LSE role of the DSO as explained in Section 4.2.1.2.

To participate in the wholesale day-ahead market, the DSO uses the results of the retail day-ahead market corresponding to the next day 24 hours. The 24 retail market price-quantity curves are converted to wholesale prices and the DSO uses the LMP forecast of wholesale prices at its point of connection to the transmission system to determine a fixed-load bid for each of the 24 wholesale market hours.

This implies that participating customer price sensitivity is not included as a price-sensitive curve for wholesale market resolution with generator price-sensitive curves in the DSO+T study. Price sensitivity is included to some degree by the DSO's use of the LMP forecast to enter a fixed-load bid; however, future investigations should consider DSO wholesale market participation with submission of price-quantity demand curves.

For the wholesale real-time market, the DSO uses the price-quantity curve resulting from the retail market, translates the curve to wholesale prices and uses the LMP forecast for the real-time interval of the hour to enter a fixed-load bid to the wholesale market. As in the wholesale day-ahead market bid, a future improvement is for the DSO to enter a price-quantity demand curve into the wholesale real-time market. Nevertheless, the result of the wholesale market is used by the DSO to develop the retail market supply curve. The real-time volatility of wholesale market prices is passed on to the participating customers in the resolution process of the retail market.

4.2 Transactive Retail Marketplace Participants

This section describes the decision-making process and logic for the retail market participants identified in Section 2.2 for interacting with the retail day-ahead and real-time markets.

4.2.1 Distribution System Operator

As described in Sections 2.2 and 3.2, the DSO has multiple roles and responsibilities to ensure its business objective and simultaneously deliver reliable power to its customers. One of the core functions of the DSO is to establish proper information exchange between the wholesale and retail markets. The DSO represents the demand from its customers to the wholesale marketplace and transfers the wholesale market clearing information back to the retail market operator. The various components of the DSO (distribution owner-operator, retail market operator, and LSE) go through multiple decision-making processes to realize the DSO's business objectives. The following subsections detail the decision-making processes for each component of the retail DSO.

4.2.1.1 Retail Market Operator

The retail market operator manages the market resolution processes for the retail day-ahead and real-time markets.

Retail Day-ahead Market Resolution Process

The retail market operator constructs an aggregated demand curve by summing the price-quantity bids based on the offered price as illustrated in Figure 15. For instance, the aggregated bid curve $Q_a(P=0:P_{max})$ for two participating customers (customers i and j) with their bid curves $Q_i(P=0:P_{cap})$ and $Q_j(P=0:P_{cap})$ is obtained by the algebraic sum of the $Q_i(P=0:P_{cap})$ and $Q_j(P=0:P_{cap})$.

For computational efficiency, the aggregation of all of the participating customer bid curves is done by sampling each responsive bid curve in the entire price range $(P=0:P_{cap})$. However, to accurately represent the price responsiveness of each bid in the aggregation process, the sampling steps must be finer in the price range $(P=P_{min}:P_{max})$. This is because the information in the bid curves beyond the price range $(P=P_{min}:P_{max})$ represent either minimum response $(P<P_{min})$ or maximum response $(P>P_{max})$. The process of concentrating the sampling in the price range $(P=P_{min}:P_{max})$ is important to having an aggregated price-quantity curve with enough fidelity for the translation between DSO expectation of response at a certain clearing price and the sum of the individual responses from the customer assets.

Simulations of the market have shown that the price range $(P=P_{min}:P_{max})$ generally falls only around 10% of the entire price range $(P=0:P_{cap})$. If there is not enough fidelity in the sampling, there is a risk of the deadband being skipped or truncated for individual assets. This can lead to misrepresentation of the individual bid curve in the aggregation, which leads to a discrepancy between the DSO aggregated expectation and the sum of individual customer's expected response.

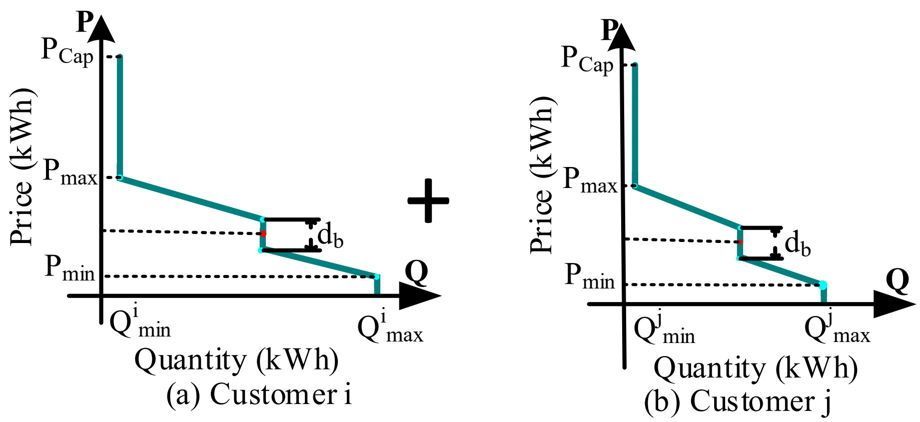


Figure 15. Illustration of bid curves aggregation process.

A diagram of the total retail day-ahead market price-response curve for hour h is shown in Figure 16 in green. The subscript d is used to contrast demand curve points from supply curve points (with subscript s) in subsequent graphs. These price-quantity bids include contributions from the participating customers' responsive and nonresponsive assets. In addition to the aggregated price-sensitive bids, the retail market operator receives the forecasted load from the LSE on behalf of nonparticipating customers. The aggregation of the forecasted loads for nonparticipating customers together with the aggregated responsive bids represents the DSO demand curve. That is, the price-responsive portion of the curve is supplemented with the amount of nonresponsive load forecasted for that hour.

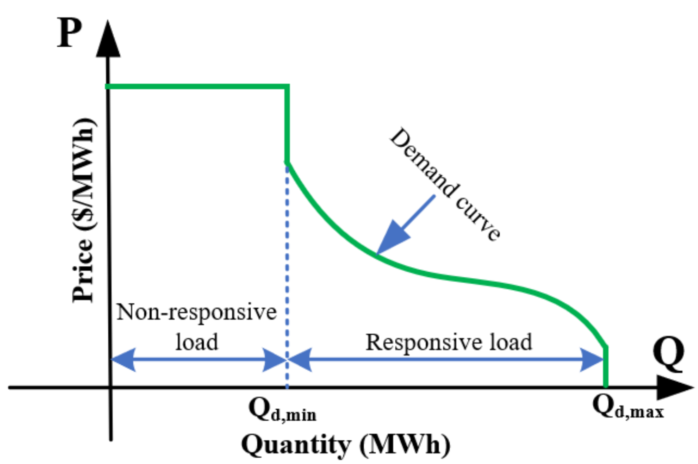


Figure 16. Total price-response curve for retail day-ahead market for hour h.

In the general design of the market process, the retail market operator constructs the supply curve utilizing the DSO's decision process that uses its interactions with the wholesale day-ahead and real-time markets. In addition, the capacity limit for the distribution circuit obtained from the distribution owner-operator is incorporated to represent the maximum quantity for the circuit for that hour.

For the DSO+T study's retail day-ahead market implementation, each DSO uses an LMP forecaster to estimate the wholesale LMP at its transmission node in its formation of the supply curve. The process of LMP forecasting is described in Section 4.3.2.

Figure 17 shows the formation of the red supply curve, which has two parts:

1. The horizontal red line represents the locally uncongested region that corresponds to the retail expression of forecast wholesale market clearing price (from LMP forecaster) as a function of quantity plus a fixed volumetric charge to cover distribution system expenses.
2. The vertical red line represents the constrained region in which the delivered quantity of energy for the market interval should not exceed the transport constraints of the power delivery system. In the DSO+T study's implementation, it is represented as the capacity limits of the substation transformer.

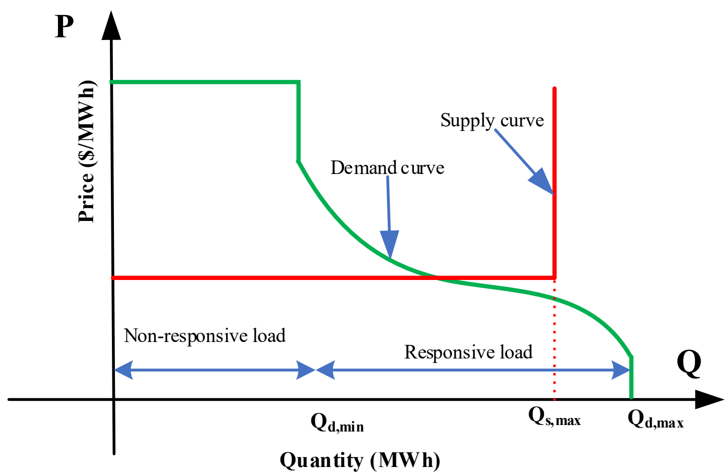


Figure 17. Retail day-ahead market for hour h with supply and demand curves.

A double-auction market mechanism is used for retail day-ahead market clearing where the point for hour h is obtained from the intersection between the aggregated demand bids (green curve) and retail supply curve (red curve) in Figure 18. Because the retail day-ahead market window is 48 hours, the retail DA market is cleared for the next 48 hours. The marginal price of energy cleared in the market is represented by P_{clear} in Figure 18.

The retail DA market is said to be converged as long as the aggregated demand curve and supply curve intersect. In the case when the aggregated demand and supply curves do not find a crossing, the retail DA market results in an infeasible solution where there is not enough supply to meet the unresponsive demand. In the real world, if the nonconvergence was caused by the delivery capacity limit, the associated substation equipment (such as the distribution circuit transformer) would be loaded beyond its rating. That can result in loss of equipment life, or in extreme situations, equipment failure and loss of power.

A core objective of the retail transactive market design is to manage energy delivery constraints at both the transmission and distribution levels of the system. The benefit is to defer or avoid required infrastructure upgrades. The retail DA market considers transmission-level constraints through the prices the DSO experiences in the wholesale market LMPs. This is represented in the horizontal portion of the red line in Figure 18. When the retail DA market clears on this portion of the supply curve (the uncongested case in Figure 18), the price-sensitive loads are responding to the wholesale market fluctuations augmented by any transmission congestion.

When the distribution circuit is constrained (the congested case in Figure 18) the retail day-ahead market clears on the vertical portion of the supply curve. This causes an increase in the marginal price of energy to the participating customers, which incentivizes them to reduce demand.

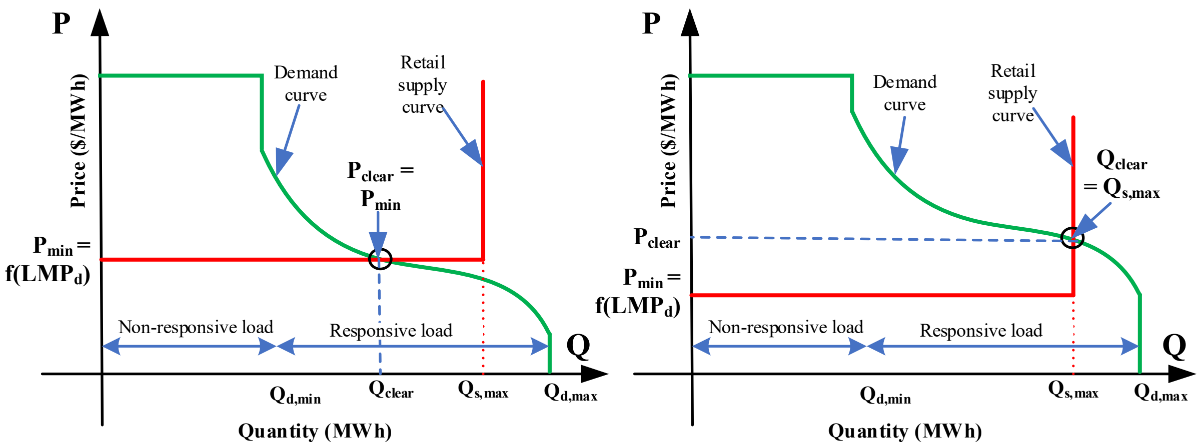


Figure 18. Market clearing for the uncongested (left) and congested (right) cases.

Observe that there must be enough flexibility in the responsive region of the demand curve to manage the constraint, i.e., $Q_{d,min}$ must be less than $Q_{s,max}$. When the flexibility being offered by the responsive assets is no longer sufficient ($Q_{d,min}$ is greater than $Q_{s,max}$), or when a cost-benefit analysis determines that the cost of congestion exceeds the costs of the upgrade, a local distribution capacity upgrade is warranted. In the DSO+T study, such an upgrade is presumed to have proceeded so that the market always converges to a clearing.

The process of converting the wholesale day-ahead market supply curve to a retail market supply curve involves combining the forecast wholesale LMPs into the transactive rate design that is discussed in Section 4.2.1.2. Note that the increased retail prices used to manage distribution congestion require a process for calculating the compensation to participating customers for paying higher prices during congestion periods (i.e., a congestion rebate) are presented in the retail rate design of Vol. 4 (Pratt, et al. 2022).

Retail Real-time Market Resolution Process

As described in the retail real-time negotiation process in Section 3.2.3, the retail market operator collects price-quantity bids every 5 minutes and aggregates them together with the forecasted loads of all nonparticipating customers received from the LSE. The nonparticipating load forecast is performed hourly. Therefore, the forecasted load for nonparticipating customers remains the same for any hour. To avoid hourly jumps, each real-time market interval linearly interpolates the nonparticipating load quantity from the LSE as described in Section 4.2.2. Similar to the aggregated curve shown in Figure 17 for the retail day-ahead market, the price-responsive portion of the aggregated demand bid for the retail real-time market will be offset by the forecasted nonresponsive loads for that market period.

The process of constructing the real-time supply curve by the retail market operator is similar to the process for constructing the day-ahead supply curve. In the real-time supply curve, the price corresponding to the horizontal red line in Figure 17 is based on the wholesale real-time LMP. The horizontal component of the curve is determined by a function of the wholesale market LMP at the DSO's transmission node (P_{min} = f(LMP)) and the capacity limits, from the distribution owner-operator in the vertical component of the curve, reflect the physical limit of the substation transformer ($Q_{s,max}$). This limit is directly related to the maximum power capacity but is converted to a quantity of energy, $Q_{s,max}$, by multiplying the maximum power by the time duration (5 minutes) of the market window. While the capacity limit is a static parameter reflecting the physical limit of the substation transformer, the P_{min} varies dynamically as a function of the variation in the wholesale LMP.

A double-auction market mechanism is used for the retail real-time market and the clearing point for the market period is obtained from the intersection between the aggregated real-time demand bid and retail supply curve (similar to the day-ahead retail market clearing shown in Figure 18). The market result converges at the point of intersection.

The process of handling transport congestion in the retail real-time market is similar to the one described for the retail day-ahead market. For the distribution uncongested case, the market clears on the horizontal portion of the supply curve that corresponds to the wholesale real-time price. In this case, the responsive loads react to the wholesale market LMP fluctuations, which includes incentives to mitigate transmission constraints. However, when the distribution system is in a congestion situation, the market clears on the vertical portion of the supply curve. This results in increasing the retail real-time cleared price and reduces demand.

4.2.1.2 Load-Serving Entity

The LSE forecasts the demand for nonparticipating customers and represents their energy needs in the wholesale and retail marketplace. For the retail marketplace, the LSE provides the forecast demand of the nonparticipating customers for the retail market operator to construct the demand curve used to clear the retail market. Similarly, for wholesale marketplace participation, the DSO assembles demand curves based on the demand cleared from the retail market operations to purchase the electricity from the wholesale marketplace. In addition to the load-forecasting function, the LSE services the rate schedules for customers, measures customer use, and bills customers. The load-forecasting function of the LSE is described in detail in Section 4.3.3 and rate-making functions of the LSE are described briefly next.

A detailed treatment of the transactive retail rates, as well as an example of the BAU rate structure, can be found in Vol. 4, Section 4 (Pratt, et al. 2022). This section provides a summary of the formulation of the transactive rate design to enable a better understanding of the structure of the dynamic transactive retail rate signal. A core tenet of the transactive rate design is that customers see a reduction in their electric bills in proportion to the actual value the DSO derives from their response. The participating customers' electric bills reflect the cost basis of the DSO and is structured in four components (independent of customer class, substation constraints, or DSO):

$$Bill = EnergyCost + CongestCost + DistributionCost + MeterCharge \tag{4-1}$$

where:

EnergyCost – this is the *wholesale* dynamic energy cost of a customer's consumption, reflecting the wholesale terms (LMP-related terms) in the DSO cost structure, plus distribution losses (since they do not appear in the customer metered load). The DSO+T study assumes that participating customers purchase the entirety of their forecast quantity in the day-ahead market (at cleared wholesale market prices plus distribution markup) and that only the difference between forecast quantity and actual load is settled in the real-time market.

CongestCost – the marginal retail congestion costs associated with *peak capacity* at a substation's retail market node, reflecting the peak capacity terms in the DSO cost structure as the cost to utilize flexible loads and DERs to manage the DSO's local and global constraints. A rebate is applied to ensure that the distribution congestion charge is revenue neutral.

DistributionCost – the *volumetric* distribution system costs, reflecting the elements in the DSO cost structure that are appropriately allocated to customers based on the relative size of their volumetric energy consumption but not the wholesale price. That is, a constant energy price term added to the customer bill over and above the retail market clearing price.

MeterCharge – the *constant* (monthly) charge reflecting the constant terms of the DSO cost structure.

This rate structure is used to develop a dynamic price signal that can optimize the quantity of day-ahead and real-time energy commitments. The resulting dynamic price signal is shown below:

$$Price(t) = A * LMP(t) + DCP(t) + D \tag{4-2}$$

The retail multiplier (*A*) is estimated based on the typical losses seen in distribution systems. The congestion pricing (*DCP*) is automatically determined by the clearing of the retail market during the simulation. The volumetric distribution energy price (*D*) is estimated based on distribution costs calculated in the BAU case. This price is multiplied with the day-ahead and real-time customer quantities and is summed over the billing period. A congestion rebate is then applied to redistribute the revenues associated with the distribution congestion pricing. Once the fixed monthly meter charge is applied, the customer bill in Equation (4-1) is obtained. Please note the same rate design applies to all DSOs and their customers in the simulation.

4.2.2 Participating Customer Agent

Each participating customer manages the operation of assets at a site (that is, behind a customer meter). As shown in Figure 19, a software agent associated with the site acts on behalf of the customer to collect price-responsive bids from all the responsive assets and to forecast the demand of the nonresponsive assets. The price-responsiveness of the participating customers is reflected in the price-quantity bid curves they submit to the retail marketplace.

These bid curves are derived from the customer's preferences for balancing the utility of energy (for comfort or other objectives) with electricity cost. The participating customers provide their comfort and flexibility preferences and use market participation strategies such as energy arbitrage and hedging between retail day-ahead and real-time markets. Such sophisticated strategies are expected to be provided by their retail service providers or facility energy management experts.

Each responsive asset prepares its price-responsive bids and the customer's site agent is responsible for assembling the bids from the responsive and nonresponsive assets within its site. As described in Section 4.3.3, each participating DSO+T customer estimates the energy needs of the nonresponsive assets in the same way the LSE estimates the load of the nonparticipating customers. The generic process that each responsive asset uses for the decision-making process is described next.

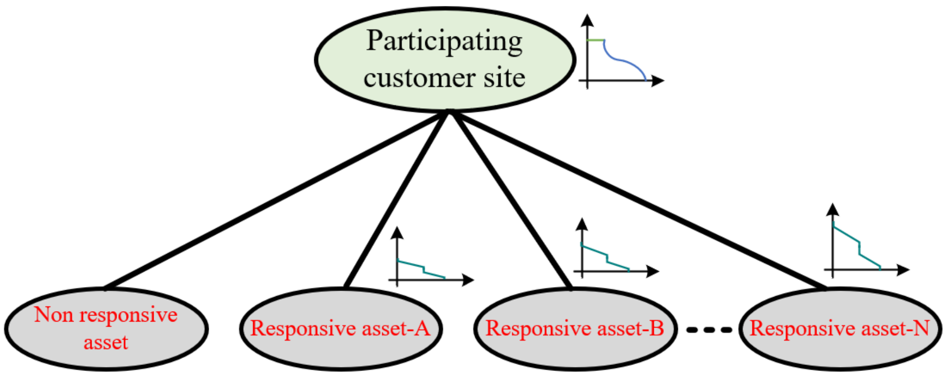


Figure 19. Participating customer function.

4.2.2.1 Generic Responsive Asset Agent

Figure 20 illustrates a high-level schematic that provides a generic decision-making process of the responsive asset. Since each asset can have different physical behavior, operating modes, and operational constraints, this section provides a generic overview of how participating customer's responsive assets are designed. The details of the specific implementations and physics of each asset type are described in later sections.

Each responsive asset agent is designed with four core components:

1. **Asset agent model** estimates the physical behavior of the respective DER asset based on observed sensor measurements
2. **Asset scheduler** prepares an operating plan for the respective asset considering the forecast future prices and asset constraints (e.g., comfort setting preferences)
3. **Asset bidding** prepares a price-quantity curve for the respective responsive asset to participate in the retail market
4. **Market control mapping** maps the real-time price into the control settings for the given asset.

In addition to these core components of the responsive asset decision-making framework, Figure 20 also illustrates the interactions between the responsive asset agent with the actual asset (e.g., HVAC, electric water heater, battery, EV). The interactions between the responsive asset agent and the actual asset are maintained through two signals: monitoring and control. The asset agent monitors measurable parameters from the asset using the predefined signals. Those monitored signals are used to estimate the operating state of the asset. The asset state is used to prepare bids for the retail market. The retail market provides a price signal that is used by the asset agent to compute the control signal sent to the physical resource controller. The controller operates the physical asset to achieve the desired effect.

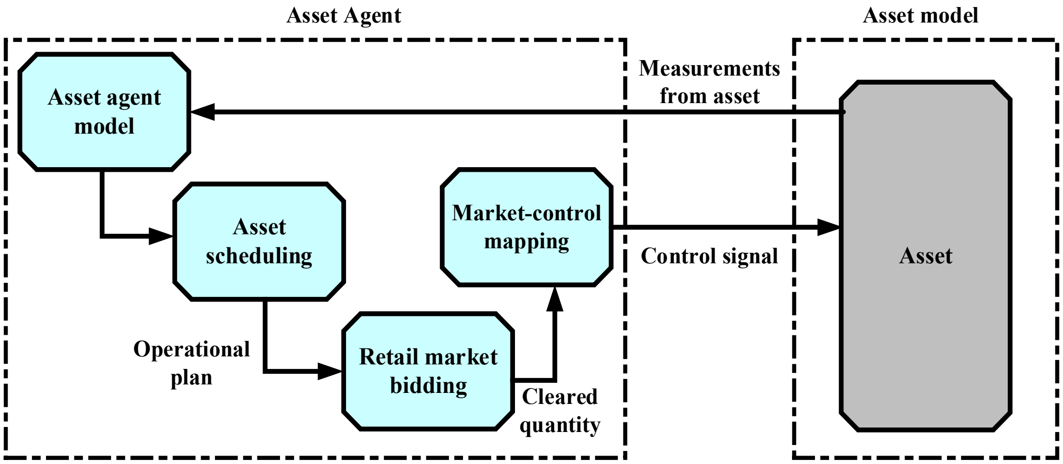


Figure 20. Overview of a responsive asset agent.

The responsive asset agent acts as a supervisory control layer to the physical asset. Therefore, all asset-specific inner loop controls and associated protections will still be active and supersede the control action from the responsive asset agent to protect the health of the equipment and ensure physical constraints are not violated. For instance, if an HVAC unit has not met its minimum on/off-time, it will not change state (on to off or vice-versa) even if signaled to do so by a supervisory control temperature setpoint change. The following subsections detail each of these functions.

Asset Agent Model

As a supervisory controller, the responsive asset agent monitors selected operating parameters of the physical asset as well as weather parameters such as ambient temperature and solar irradiance from the weather forecaster. To understand the operating state of the physical asset, the agent model estimates the asset's dynamics from the monitored parameters. The modeled physics and parameters monitored can vary for each asset type. For instance, the monitored parameters to calculate state of charge (SOC) for an EV are completely different from the monitored parameters to understand the operating state of the HVAC unit. Moreover, the dynamics of EV operation can be significantly different compared to that of the HVAC unit. The details of the specific asset model estimation are presented in the respective asset agent subsections.

Asset Scheduler

The scheduling function computes an operational plan for the responsive asset considering the forecast electricity prices received from the retail market, asset operational constraints, and user preferences (e.g., desired comfort level versus cost savings). The scheduling function determines an operational plan that strives to balance the tradeoff between the price of energy and the amenity (e.g., occupant comfort) received from its use over a scheduling time horizon. The consumer's sensitivity preference between price and amenity is expressed in the form of a slider setting, ω, that ranges from 0 to 1.

As shown in Figure 21, a slider setting of '1' means the customer is primarily concerned with cost savings. Therefore, the customer with slider settings of '1' provides maximum flexibility to operate the asset in response to price changes. A slider setting of '0' means the customer prioritizes comfort irrespective of the electricity price. Hence the asset is devoted to achieving the desired amenity and has no flexibility to respond to price changes. Customers who have a slider position between 0 and 1 vary the relationship between full and no operational flexibility. An advantage of the slider-based preference approach is its simplicity. Customers can change their sensitivity between comfort and price by moving the slider position and experience their satisfaction with the results of their decisions without knowing the internal operational details.

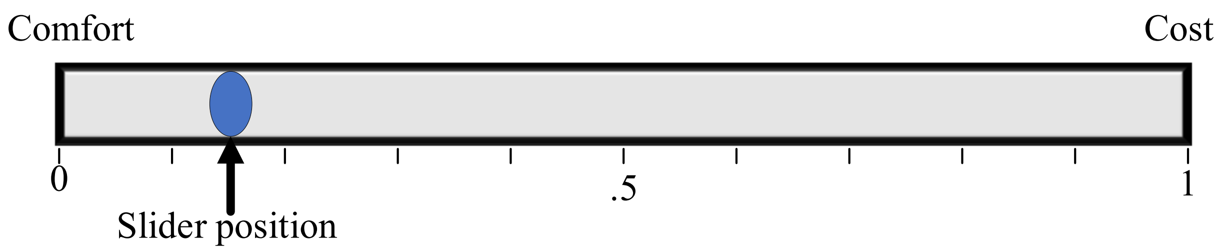


Figure 21. Slider representation.

The following represents a generic operational scheduling formulation applicable to all assets. The result of this optimization is an operational plan.

$$\min Cost = min \sum_{t=1}^{T} [\{\omega * P(t) * Q(t)\} + \{(1-\omega) * Discomfort\} - \{\beta Q(t)^2\}] \tag{4-3}$$

Where:

Cost: the total cost of operating the responsive asset over the time horizon (USD)

ω: slider position (unitless)

P(t): forecast price per unit energy for time *t* (USD/kWh)

Q(t): electricity quantity to be traded for time *t* (kWh)

Discomfort: a function representing the cost of discomfort (USD)

β: smoothing coefficient used to moderate control action volatility between time intervals (USD/kWh^2)

T: time horizon of the operational plan of the given asset (days)

t: the time period (hours)

Discomfort is expressed as a function of deviations from the desired operating point. For instance, in the case of an HVAC asset, the discomfort is expressed in terms of how far the room temperature deviates from its desired setpoint multiplied by the price per unit deviation. Each asset has its own discomfort function.

The output of the scheduling function is an operation plan: a set of hourly desired operational schedules for the next 48 hours. The plan is used as a point of reference for market participation decisions. Note that each responsive asset type has a different model, operational dynamics, and operational constraints. Therefore, the mathematical formulation needs to be tailored to the specific asset type. The detailed scheduling function for each asset type is presented in their respective asset agent description sections that follow.

Retail Market Bidding

This subsection presents the overall process to form retail day-ahead and real-time market bids by participating customers. For the day-ahead participation, each responsive asset uses its operational plan and prepares a price-quantity bid utilizing the forecast retail electricity price for the next 48 hours.

As shown in Figure 22, a linear price-responsive curve is computed using the forecast price and the asset operational limits.

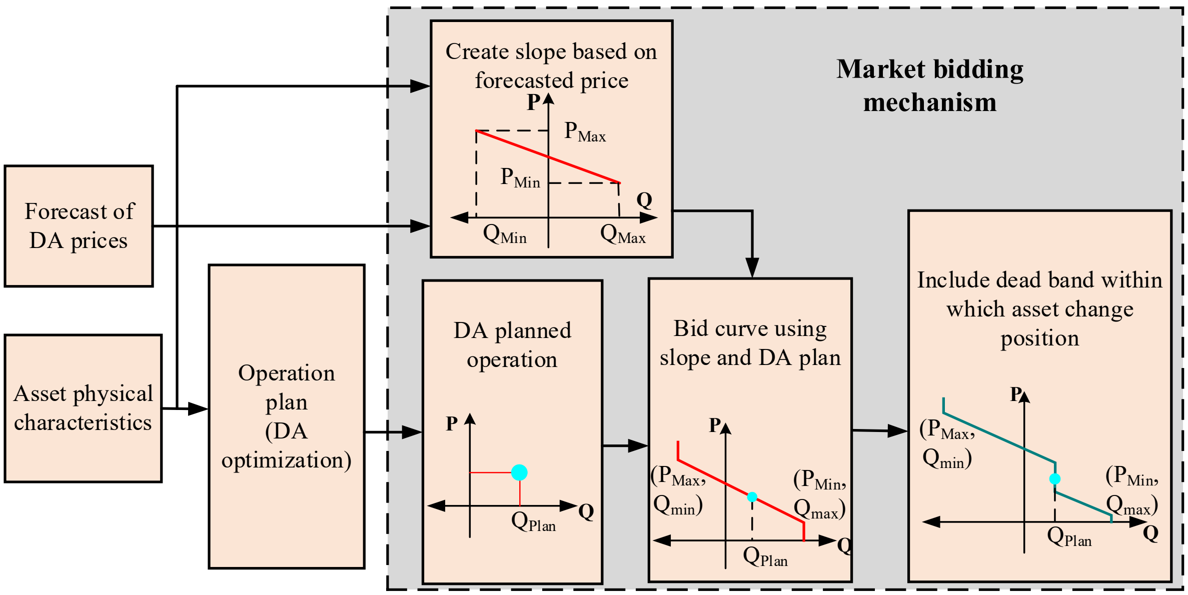


Figure 22. Responsive asset bid formation process.

The price-responsive bid curve is calculated at every retail day-ahead market interval, *t*. The slope of the curve is computed using the following formula:

$$\text{Slope} = \frac{1}{\omega S}\frac{(P_{max}(t) - P_{min}(t))}{(Q_{min}(t) - Q_{max}(t))} \tag{4-4}$$

Where:

slope = slope of the bid curve (USD/kWh)
ω = slider position (unitless)
P_{max} = maximum forecast price in the given horizon (USD)
P_{min} = minimum forecast price in the given horizon (USD)
Q_{min} = minimum quantity the resource can consume/produce (kWh)
Q_{max} = maximum quantity the resource can consume/produce
t = market interval (hours or minutes)

The slope obtained from this step is combined with the scheduled desired point from the operational plan to form the bid curve as shown in Figure 22. To account for the physical limits of the DER flexibility, quantity limits are inserted. Finally, a price deadband is introduced around the desired operating point so the asset agent avoids sending control signals to the asset controller for minor price changes. This deadband avoids jitter, which can cause wear and tear of the equipment for needless operation. Systemically, it also induces stability in the price discovery and allows price-responsive agent to stay close to their preferred operating plan.

In the retail real-time market, the responsive asset agent starts with the bid curve developed for the most recent retail day-ahead market hour that corresponds with the real-time 5-minute market interval. The agent updates this bid curve to reflect what the asset can do in the next retail real-time market 5-minute interval. For instance, a responsive asset forms its retail real-time market bid curve for the 10:25 a.m. market interval by taking the retail day-ahead market bid curve for the 10 a.m. interval and calculating the upper (b) and lower (a) operational limits that the asset can travel from the given operating point Q_{plan} in the 5-minute interval, as shown in Figure 23. These operational limits are calculated based on real-time conditions of agents, detailed later in the individual agent implementations. Even though the responsive asset agent uses the same price-responsive curve from the day-ahead bid curve, the range of the curve may shorten due to the 5-minute operational constraints of the asset. This change in range of the curve reflects real-time conditions of the responsive asset agent.

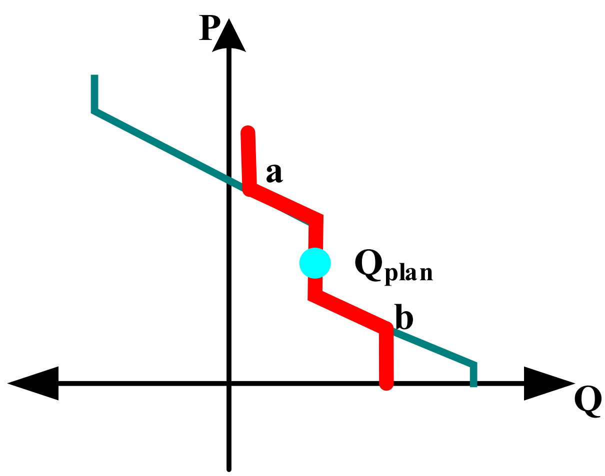


Figure 23. Real-time bidding of the responsive asset.

Therefore, if a participating customer's retail day-ahead market-cleared quantity is 'Q_{H1}' for the hour H_1, the customer will make its retail real-time market price-quantity bids for the twelve 5-minutes market intervals to stay close to (P, Q_{H1}), its planned price quantity. However, this approach can result in hourly step changes in the agent's 5-minute real-time responses. When exhibited by a large fleet of assets it can result in unintended synchronization of the fleet response causing very large increases or decreases in load during the first 5-minute interval of each hour (Figure 24). To ensure a smooth transition between the hours, the reference point is updated every 5-minute market interval using a linear interpolation of the retail day-ahead market-cleared quantity as illustrated in Figure 25. This approach interpolates between the middle of each hour to ensure that the overall bid quantity is maintained. As long as the retail real-time market-clearing price is within the price deadband, the responsive asset follows the day-ahead operational plan. However, if the retail real-time market clears beyond the deadband price range, the asset will move away from the planned operating quantity in its day-ahead plan.

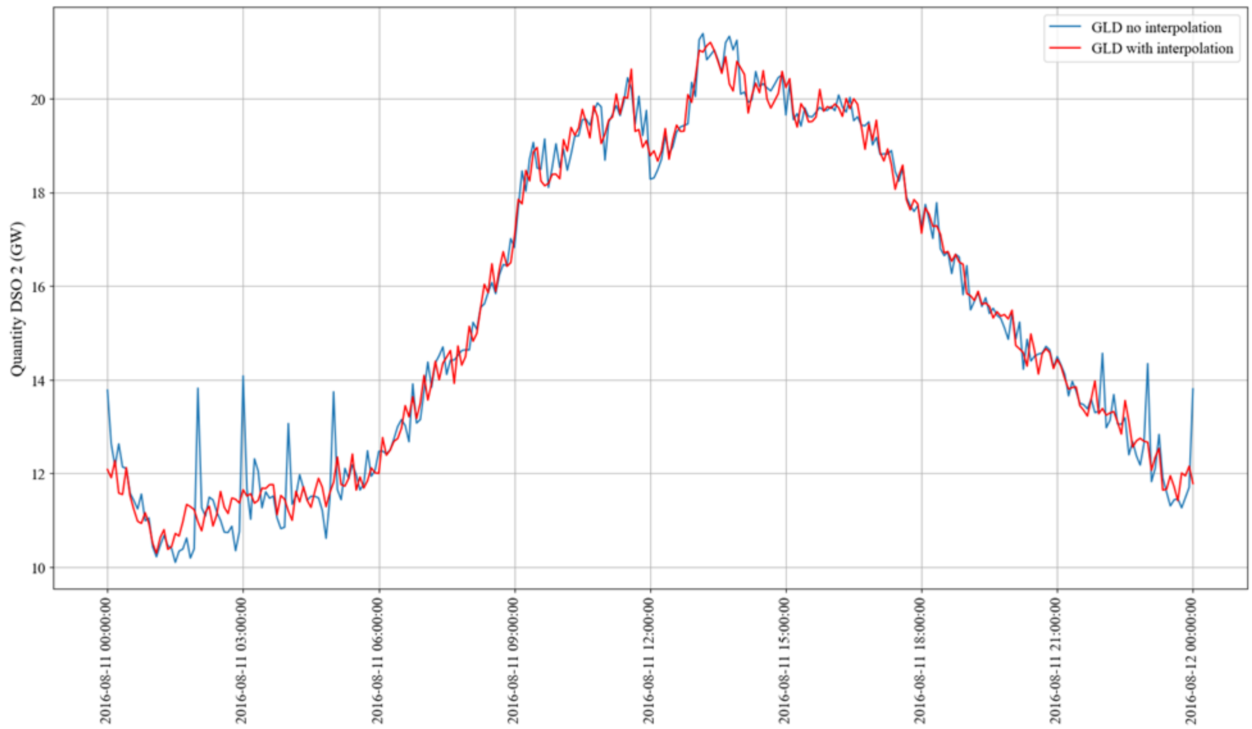


Figure 24. Example of simulated daily load profile for DSO 2 with and without interpolation of the hourly bid strategy when used as the basis for real-time response strategy.

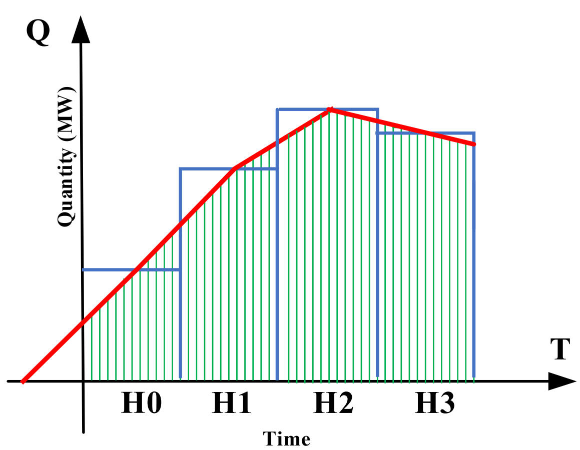


Figure 25. Interpolation of day-ahead quantity for reference to real-time bidding.

Market Control Mapping

Once the responsive asset agent receives the cleared price from the retail real-time market, it maps the cleared price into the setpoint signal to the asset controller. In the case of the battery, the cleared price is mapped directly into charging/discharging quantity using the bid curve; whereas, in the case of the HVAC and water heater, the cleared price is translated into the temperature setpoints for the thermostat. The details of the mappings for each asset type are presented in Sections 4.2.2.2 through 4.2.2.5.

Information Monitoring

Because each responsive asset agent is designed to act as a supervisory controller for the corresponding asset that is implemented in the field or modeled in software tools (such as GridLAB-D), the asset agent needs to interact through the asset model's defined set of inputs and outputs parameters. The interface between the asset agent and corresponding asset (either real equipment or simulation model) is defined considering the following aspects:

- Number of variables being exchanged
- Variable type (e.g., feedback, control, instantiation)
- Range of values for each variable
- Frequency of data exchange (e.g., retail real-time market signals are read every 5 minutes, power-flow-related signals are exchanged every 15 seconds).

The primary purpose of the interface is to decouple the agent decision-making from the device-specific controls and physical system. This ensures the device-specific inner-control loop takes precedence over the supervisory control action from the asset agent.

4.2.2.2 HVAC Transactive Agent Design

The HVAC asset agent is designed as a supervisory control to the HVAC asset. While executing the supervisory control action, it performs four core functions: model estimation, scheduling, market participation, and control implementation. The HVAC agent, therefore, provides a control setpoint to the HVAC asset. Please note that the HVAC itself has a local thermostatic controller that switches the HVAC system on and off based on the given control settings received from the HVAC agent.

Market participation is one of the core functions of the transactive HVAC agent, enabling participation in the retail day-ahead and real-time markets. The day-ahead bids contain the expected operational plan for the next 48 hours, which in turn is used as a baseline for the real-time agent market participation (e.g., its behavior). Every 5 minutes with updated local information, the HVAC agent generates its retail real-time market bid curve knowing the latest 48-hour operational plan. This also takes into consideration the HVAC system limitations and customer comfort preferences, dictated by setpoint deviation from the desired temperature schedule. Once the retail market is cleared, the real-time bid curve is used to convert it into a new temperature setpoint signal for the HVAC's thermostat.

HVAC Model

The model of HVAC system dynamics captures the overall heat transfers of the building. The main components in the system are the house (building), the air inside the house, and the external environment (represented by outdoor temperature and solar irradiance); the air temperature inside the house is a result of energy exchange between those components. A common approach lumps the system components to minimize the data required but maintains a reasonable accuracy (Ihara, 1981). This full detail second-order equivalent thermal parameter model used in the GridLAB-D simulation to compute the indoor air temperature (Black 2005). The model components are demonstrated as circuit elements in Figure 26.

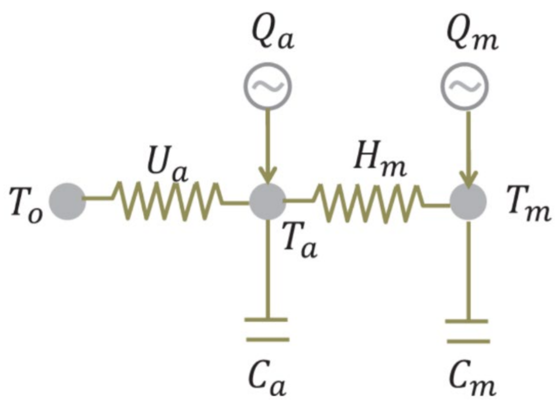


Figure 26. HVAC second-order equivalent thermal parameter model representation with circuit elements.

The differential equations representing the second-order equivalent thermal parameter model, described in (Chassin et al. 2008), are as follows:

$$
\begin{aligned}
C_A \frac{d}{dt} T_A &= q_A - U_A(T_A - T_O) - H_M(T_A - T_M) \\
C_M \frac{d}{dt} T_M &= q_M - H_M(T_M - T_A)
\end{aligned}
\tag{4-5}
$$

Where:

T_a is the ambient (indoor) air temperature (°F)

T_M is the building mass temperature (°F)

T_O is the outdoor air temperature (°F)

q_A is the heat gains added to the indoor air (BTU)

q_M is the heat gains added to the building mass (BTU)

C_A is the heat capacity of the indoor air (BTU)

C_M is the heat capacity of the building mass (BTU)

H_M is the building mass conductivity to the indoor air (BTU/°F)

U_A is the building envelope of conductivity to the indoor air (BTU/°F)

However, this model is second order which makes optimization (discussed in the next subsection) challenging and causes simulation scalability performance issues. To evaluate the HVAC energy consumption for the future market interval (48 hours), the simulation needs a simplified model that provides a reliable estimate with a limited amount of information. The simulation uses a first-order model, which is derived from the second-order model by considering air and mass temperatures (T_A and T_M) to be the same. In addition, the heat capacities of indoor air and building mass are combined to become C, and the heat gains for indoor air and building mass are combined to become Q. By making this assumption, the model can be reduced to a first-order model as follows:

$$
C \frac{d}{dt} T_{room} = q - U_A(T_{room} - T_O) \tag{4-6}
$$

We then solve the differential equation model, reorder the model to fit our purpose, and introduce some variables for simplification. The first order becomes as follows:

$$T_{room}^{k+1} = \varepsilon\, T_{room}^{k} + (1-\varepsilon)(T_O - \frac{q}{U_A}) \tag{4-7}$$

Where,

C is the room heat capacity which is equal to $C_A + C_M$ (BTU)

T_{room} is the room temperature ($T_{room} = T_A = T_M$) (°F)

q is the total heat gains ($q = q_A + q_M$) (BTU)

ε is the system inertia, which equals $e^{-t\, U_A/C}$ (unitless)

The heat gains of the house are the sum of the heat gains from the HVAC system, solar heat gains, and internal heat gains from house appliances. The HVAC system heat gains (when it is on) are the result of multiplying HVAC rated power with the HVAC coefficient of performance. The solar heat gains are the results of solar irradiance and solar diffusivity inflicted on all sides of the building, multiplied by a solar gain factor that captures the building properties that affect the solar heat gains. Finally, the internal gains are the heat gains from other thermal loads (e.g., appliances) inside the house.

To validate the accuracy of this simplified model, we compare it with the second-order model used in GridLAB-D (Pacific Northwest National Laboratory n.d.). We implement the same temperature setpoint schedules and use both models to provide the HVAC energy consumption for a single house. The house parameters are listed in Table 1. The results of energy consumption from both models are shown in Figure 27. The error of the energy estimate from the first-order model is shown in Figure 28. We can observe that the error stays within 10% with an average bias less than 2% and a density that follows the normal distribution. This shows that the accuracy of the model is adequate for estimating the HVAC energy consumption.

Table 1. House parameters used for example.

Parameter	Value
HVAC rating	7 kW
C_A	1700 Btu/°F
C_M	10500 Btu/°F
U_A	891 Btu/°Fh
H_M	12800 Btu/°Fh

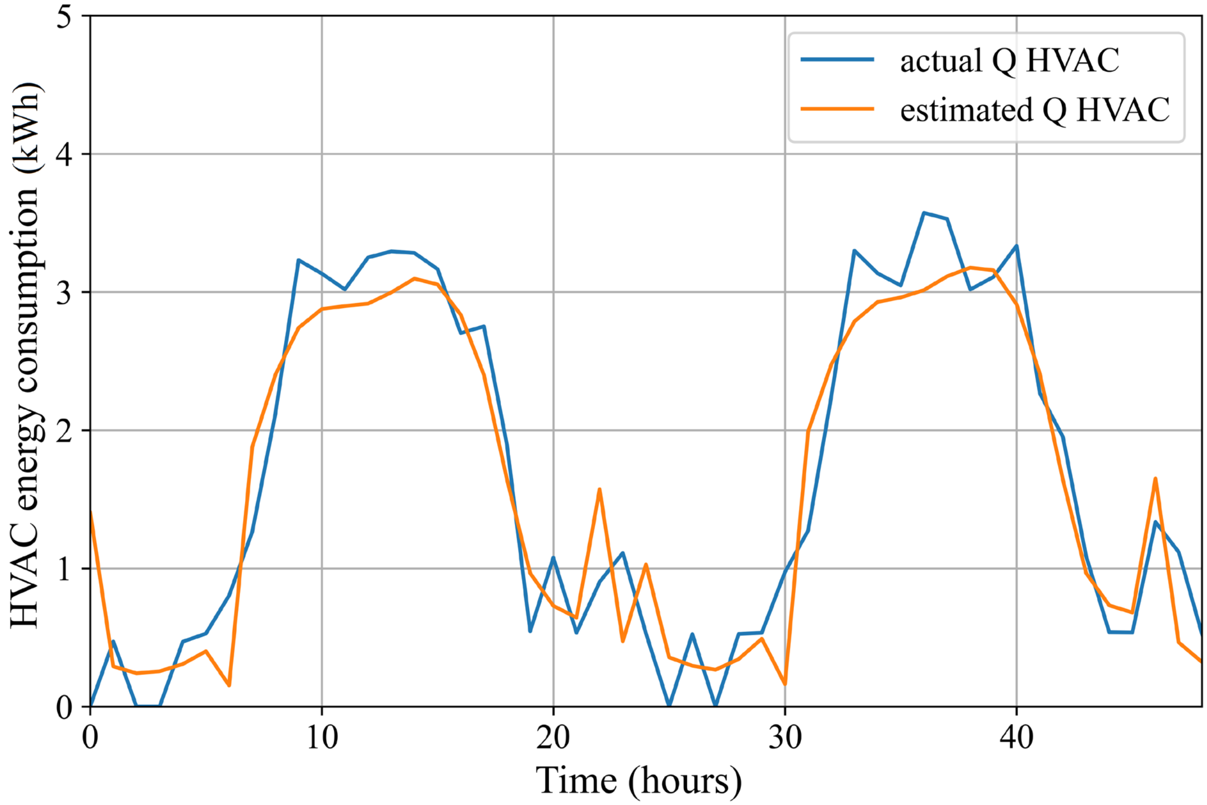


Figure 27. First-order HVAC model energy consumption comparison with second-order model.

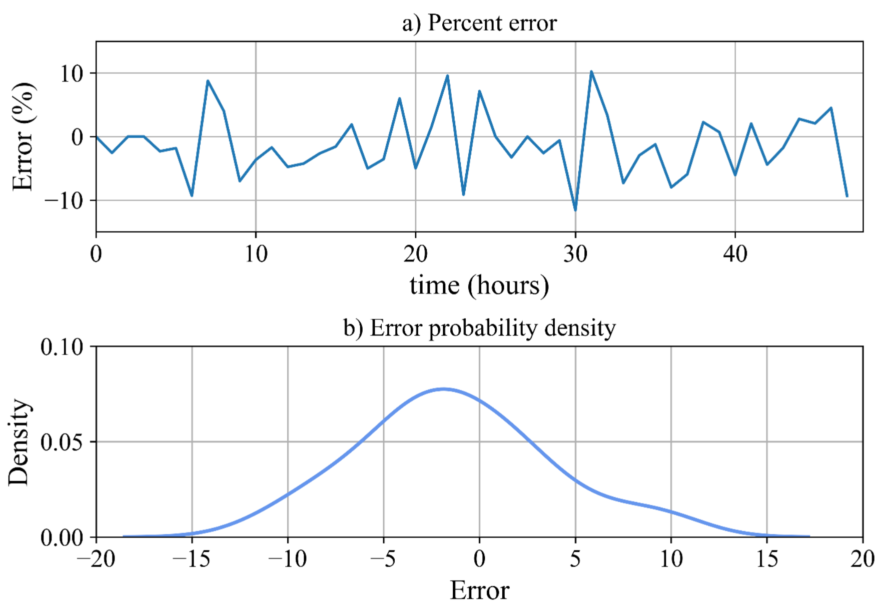


Figure 28. Energy consumption error comparison first-order vs. second-order model.

Scheduling

To maximize customer preferences for cost savings and comfort throughout the day, an operational planning model can be formulated to find the best temperature setpoint schedule that achieves these tradeoffs. A forecast of weather-related parameters (solar irradiance, outside temperature from the weather forecaster in Section 4.3.1) and house internal gains (based on appliance schedules) are used along with the first-order model to predict the HVAC energy consumption. The decision variables of the planning model are the temperature setpoint and the HVAC energy consumption, subject to the heat balance constraints introduced by the first-order model. The objective of the planning optimization is to minimize customer discomfort and customer energy costs (energy multiplied by forecast price). The objective function is described as follows:

$$\min \sum_{t}^{Time} \omega \cdot \left(\frac{P(t) - P_{min}}{\Delta P}\right) * \left(\frac{Q_{HVAC}(t)}{Q_{HVAC}^{R}}\right) + \left(\frac{T_{room}(t) - T_{desired}(t)}{T_{range}}\right)^2 + 0.001 * \omega * \left(\frac{Q_{HVAC}(t)}{Q_{HVAC}^{R}}\right)^2 \quad (4\text{-}8)$$

Where,

ω is the slider position set by the customer between 0 and 1 (see Section 4.2.2.1)

$P(t)$ is the price forecast for time t (USD)

P_{min} is the minimum price in price forecast (USD)

ΔP is the difference between maximum and minimum price forecasts (USD)

$Q_{HVAC}(t)$ is the HVAC energy consumption at time t (kWh)

Q_{HVAC}^{R} is the HVAC rating (kWh)

$T_{desired}(t)$ is the base temperature setpoint schedule (°F)

T_{range} is the range of temperature setpoint deviation that varies from $-5 * \omega \ to \ 5 * \omega$ (°F)

For each customer, the permissible range of deviation is linearly proportional to the slider setting. In this study, we used a maximum temperature deviation that is equal to +/- 5°F. To demonstrate the performance of the optimum schedule, we used the same house from the previous section with a price forecast and the forecast for other necessary quantities. For this house, the slider setting is set to 1 (i.e., +/- 5°F range). Figure 29 shows the operational plan setpoint schedule compared with the original temperature setpoint. To evaluate the total consumption in dollars, the setpoint was sent to GridLAB-D (second-order model) and the energy consumption was extracted every 5 minutes. Then the total bill was computed based on the energy consumption for that 5-minute interval multiplied with the price at the time. For operating using base schedule, the total bill for HVAC consumption is $74.57 for the 48-hour interval. However, if the HVAC operates using the optimized transactive schedule, the total bill is reduced to $65.14, which is 12.6% savings.

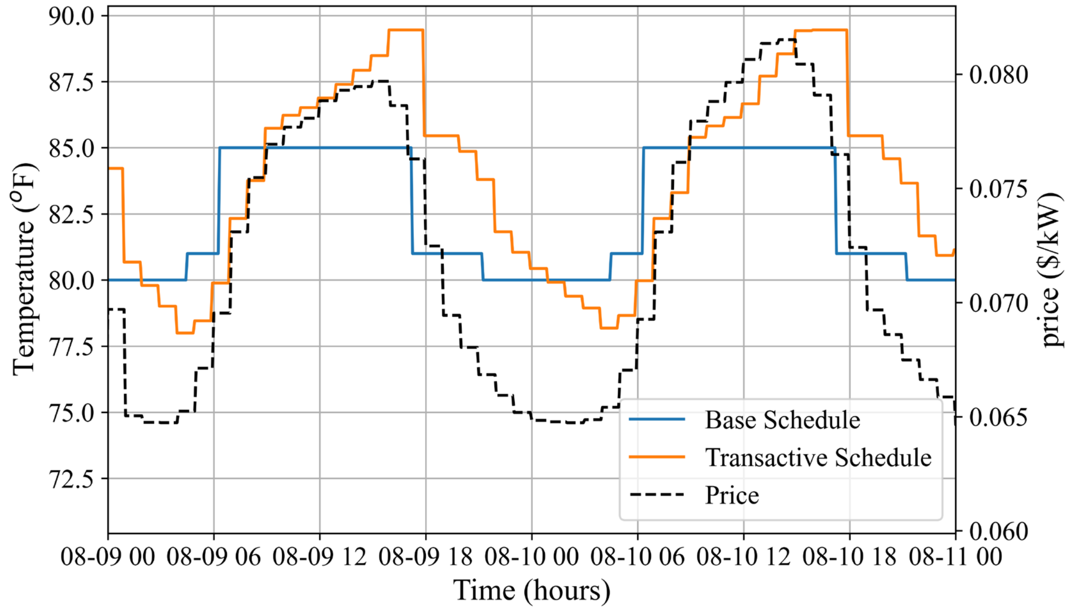


Figure 29. Operational plan setpoint schedule compared with the original schedule.

Retail Market Bidding

To provide a demand curve for the retail DA market bid, the HVAC agent uses the quantities obtained from the operational planning model. The optimal quantity and the price forecast for that hour are used as the center point of the bid. A 48 four-point bid is constructed using a deadband and slope as described in Section 4.2.2.1. For HVAC, Q_{max} is equal to the maximum energy consumption of the HVAC for that period (rating multiplied by time) and Q_{min} is equal to zero. A sample day-ahead bid for one of the hours is shown in Figure 30.

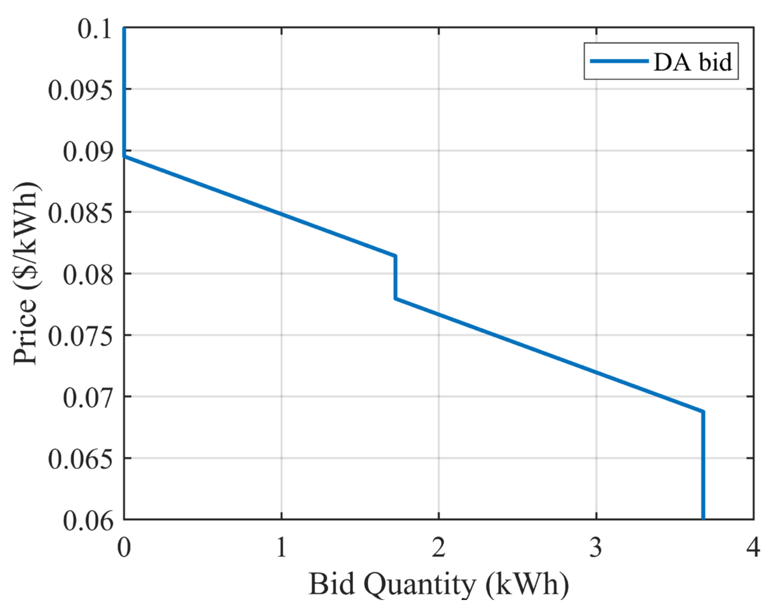


Figure 30. Sample day-ahead bid for one hour submitted by an HVAC agent.

In real-time, the bid will be centered based on the most recent retail day-ahead market planned quantity and price forecast pair for this hour. However, the retail real-time market bid curve is limited from the day-ahead bid curve using maximum and minimum quantities that can be obtained by turning the HVAC off or on, respectively, for the whole 5-minute interval. An example of the real-time bid, concerning the day-ahead bid, is shown in Figure 31.

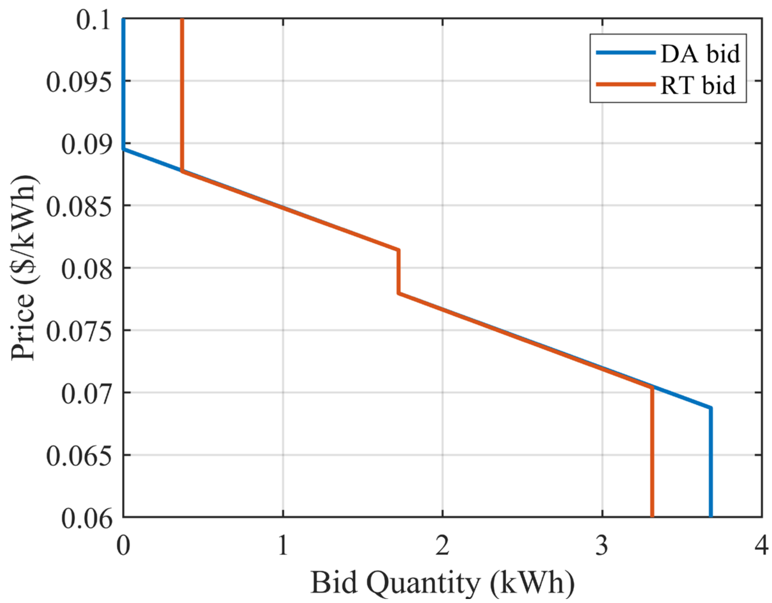


Figure 31. Real-time bid compared to the day-ahead bid produced by HVAC agent.

In addition to the real-time bid curve, the asset agent constructs a price-sensitive temperature curve that maps the temperature setpoint variation for that 5-minute interval to an energy quantity. This curve will be used to translate between the temperature setpoint, HVAC energy quantity, and the price of energy, as discussed in the next section.

Market Control Mapping

The real-time price of energy will deviate from the forecast day-ahead price due to operating conditions reflected in the market clearing. An example of this price deviation is shown in Figure 32. The operational plan HVAC temperature setpoint schedule is adjusted based on the deviation of retail real-time market price from the retail day-ahead market price. Using the retail real-time market-cleared price and the asset agent's bid curve, the HVAC's cleared quantity is extracted. To convert the cleared quantity into a temperature setpoint, an HVAC energy quantity versus temperature setpoint mapping curve is needed. An example of a temperature setpoint versus quantity curve generated for real-time operation is shown in Figure 33. The blue curve is generated from the asset model estimation of the consumption for the next 5 minutes for different setpoints. Using this curve, the cleared quantity is converted into a new temperature setpoint for the thermostat.

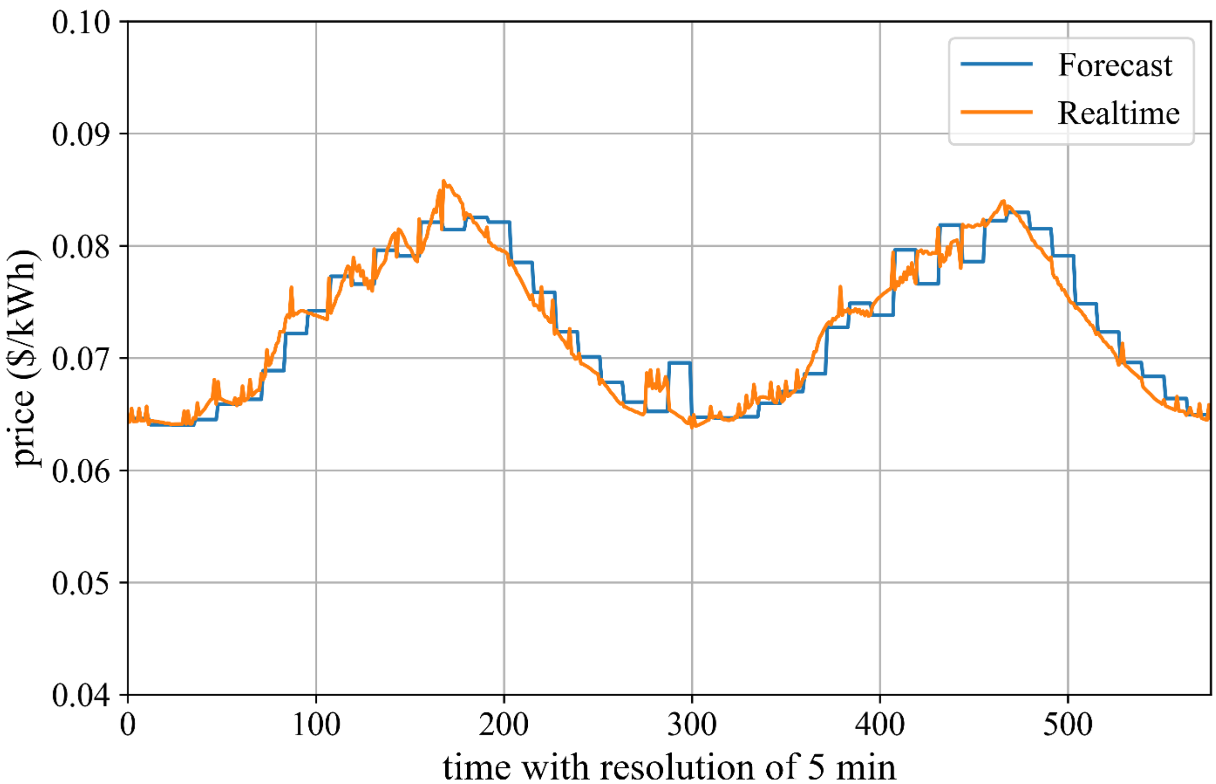


Figure 32. Day-ahead forecast price versus real-time cleared price.

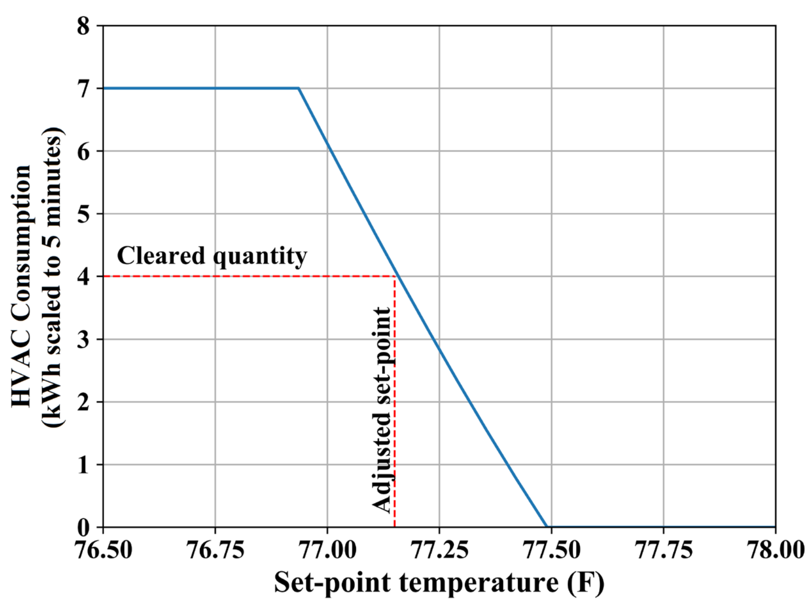


Figure 33. Real-time setpoint adjustment based on cleared price and cleared quantity.

The real-time price-sensitive adjustment enables the HVAC equipment to respond to grid needs. From the customer perspective, the adjustment reduces the electric bill because less energy is used during higher price periods. This is done at the sacrifice of comfort incurred from deviating from the desired temperature setpoint that was established based on the day-ahead cleared price. Figure 34 shows a sample simulation run for 9 August over a 2-day period. The desired setpoint schedule for a nonflexible HVAC (i.e., desired comfort fully satisfied) is in green. The operational plan established from participating in the retail day-ahead market results in a setpoint schedule shown in blue. Finally, the real-time 5-minute adjustments in the setpoint are shown in orange. In this example, the adjustment in real-time resulted in 2% additional savings from the day-ahead schedule.

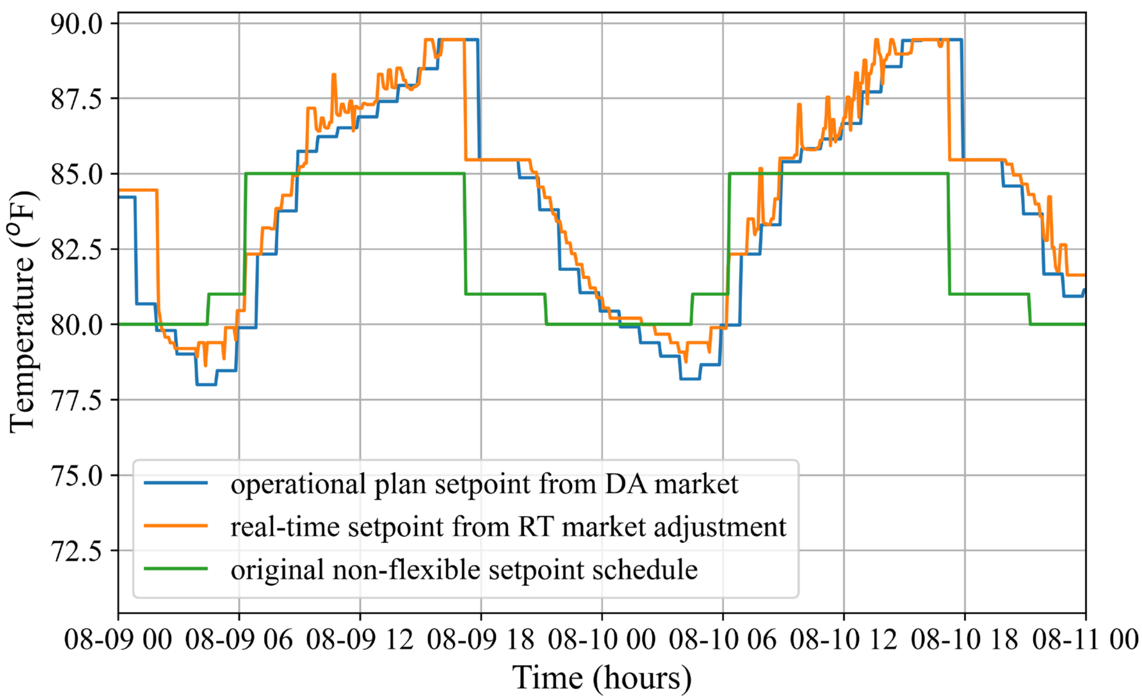


Figure 34. Real-time setpoint adjustment due to price deviation.

4.2.2.3 Water Heater Transactive Agent Design

The water heater asset agent provides transactive control to a water heater.[1] This is achieved by changing the temperature setpoints of either the lower or upper heating element of the water heater, consequently turning them on or off and shifting their consumption to a more economical period. The participating water heater purchases energy in the retail day-ahead and real-time markets by submitting price-quantity bid curves through the participating customer. The asset agent contributes the water heater bid curve and interacts with the simulated water heater. The interaction with retail market operations occurs at the frequency of market intervals (hourly for the day-ahead market and 5 minutes for real-time markets), whereas the asset agent interacts with the GridLAB-D water heater model every 5 minutes to instruct changes in its temperature setpoints. Figure 35 shows the overall interaction of the water heater agent with the market and the actual water heater. Table 2 provides notations for variables and quantities used in asset agent development.

[1] For the purpose of DSO+T, a new water heater model has been implemented in GridLAB-D. More information about the model can be found at https://github.com/pnnl/tesp/blob/develop/ercot/pdf/Fixed_Layers_Stratified_Water_Heater.pdf.

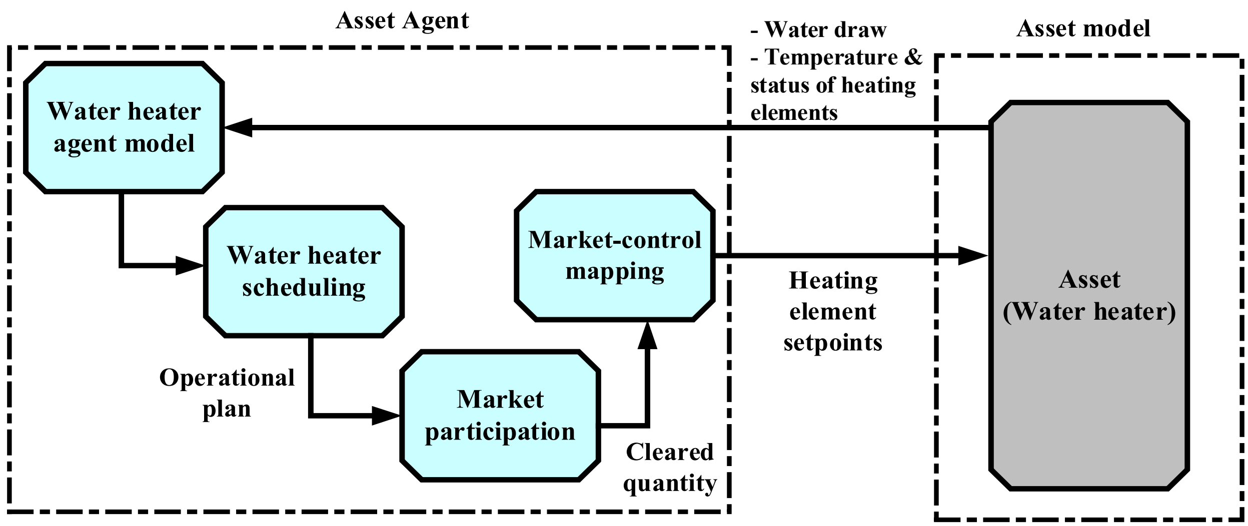


Figure 35. High-level information exchange to and from the water heater agent.

Table 2. Notations for variables and quantities used in asset agent development.

Data	Description	Unit
V_{tank}	Volume of water tank	gallon
D_{tank}	Diameter of tank	ft
UA	Heat loss coefficient from tank to ambient	$Btu/hr - °F$
ρ	Density of water	62.3 lbm/ft^3
C_p	Specific heat of water	1 Btu/lbm-°F
$BtupkWh$	Unit conversion from kWh to Btu	Btu/kWh
T_{Cold}	Temperature of cold water	°F
$T_{Ambient}$	Ambient tank temperature	°F
$T_{Desired}$	Temperature value with highest user comfort, also mixing valve setpoint	°F
T_{Max}	Highest tolerant temperature	°F
T_{Min}	Lowest tolerant temperature	°F
T_{AVG}	Average tank temperature	°F
$SOHE$	State of heat energy of the tank	unitless
w_{SOC}	Weight of upper temperature measure when estimating SOC	[0,1]
ω	Slider setting for choosing tradeoff between comfort and cost savings	[0,1]
E_{Upper} $/E_{lower}$	Energy consumed by upper/lower heating element	$[\frac{hr}{60} - min]$
Q_E	Total energy delivered by heating elements combined over hourly interval	kWh
V_{Draw}	Total water draw by water heater	gallons
Q_{draw}	Water energy drawn from water heater	kWh
P_r	Forecast retail price	$/kWh
$fr_{warwedraw}$	Forecast water draw rate	gallons
P_{rating}	Power rating of the heating element	kW
PM-I	Profit margin intercept specified in % and used to modify the slope of the bid curve	unitless

Data	Description	Unit
PM-S	Profit margin slope specified in % to generate a small dead band	unitless
P_{DA_max}	Maximum value of estimated retail hourly prices for next 48 hours	$/kW
P_{DA_min}	Minimum value of estimated retail hourly prices for next 48 hours	$/kW
$P_{DA}(t)$	Estimated retail price at hour t	$/kW
Q_{DA_min}	Minimum consumption that DER must consume for one hour	kWh
Q_{DA_max}	Highest consumption that DER could consume for one hour	kWh
Q_{opt}	Optimized quantity at hour t solved by day-ahead quantity optimization function	kWh
N	Number of sub-layers in the water heater model	unitless

Water Heater Agent Model

This section details two key functions of the asset agent: a) to estimate the state of heat energy (SOHE) and b) to control the water heater operation.

State of Heat Energy Estimation

Due to the limited observability of water heater parameters, the asset agent infers the static and dynamic characteristics of the overall heat storage level in the water tank across time. This is done through SOHE modeling of the hot water in the tank, which is parameterized with respect to the physics of the water heater model in GridLAB-D. The concept of SOHE is proposed in this study to take a water heater as an analogy of a battery, which stores thermal heat instead of electricity. It can be charged through the operation of the heating element and discharged through the water draw or heat exchange with the ambient air. In other words, when the average temperature of the water at each layer equals the desired temperature, we claim the current SOC to be 100%. The SOC of the tank ($SOHE$) at any time is then defined as the ratio of the energy of the hot water in the tank at its current temperature (relative to that of the cold-water supply), to the energy of the hot water in the tank if it was at the desired hot water supply temperature $T_{Desired}$.

$$SOHE = \frac{(T_{AVG} - T_{cold})}{(T_{Desired} - T_{Cold})} \tag{4-9}$$

Note that the mixing valve allows preheating as part of a demand-response control strategy, so the $SOHE$ can exceed 100% to a maximum expressed in the following equation:

$$SOHE_{max} = \frac{(T_{MAX} - T_{cold})}{(T_{Desired} - T_{Cold})} \tag{4-10}$$

To calculate $SOHE$, we need to know the average temperature of the tank.

If we consider N_{layer} the number of layers in a water heater, we can calculate the average temperature of the tank as $T_{AVG} = \frac{\sum_{i=1}^{N_{layer}} Ti}{N_{layer}}$. Though, the temperatures at the discretized layers of the tank are not usually known, the tank temperature at the elements is usually known. This information is used to approximate the average tank temperature as follows. The tank temperature at the upper and lower sections of the tank in proportion to their relative volumes (1/3 and 2/3, respectively) are used such that the:

$$T_{AVG} = \frac{1}{3} \times T_{upper} + \frac{2}{3} \times T_{bottom} = w_{SOC} \times T_{upper} + (1 - w_{SOC}) \times T_{bottom} \tag{4-11}$$

Figure 36 shows that the estimated $SOHE$ using equations (4-9) through (4-11) follows the actual $SOHE$ change calculated using the temperatures of 10 layers of a water heater modeled in GridLAB-D (Bhattarai et al. 2020b).

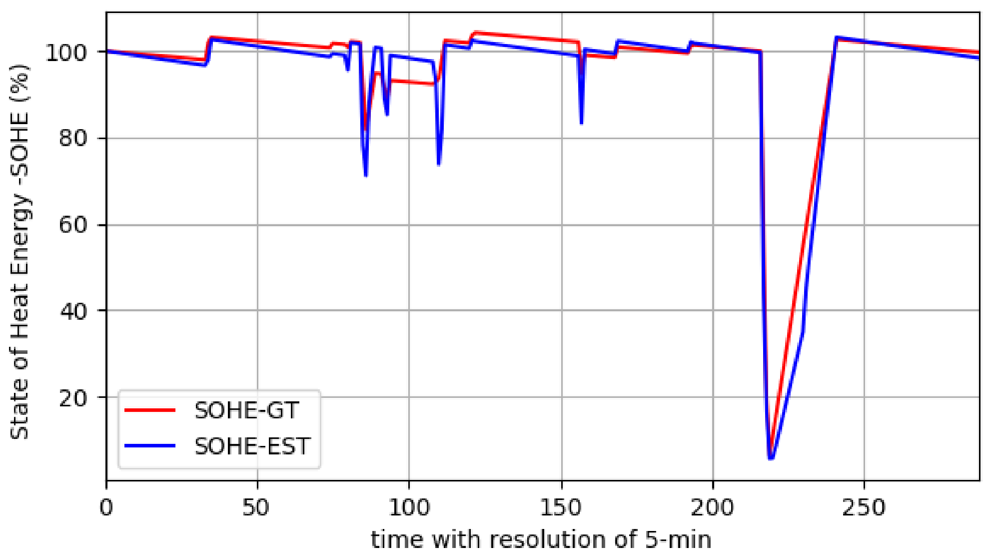


Figure 36. SOHE estimation (GT: ground truth, EST: estimated).

Unlike a battery, the water heater cannot control the “charging rate” of the $SOHE$ directly. Instead, the change in $SOHE$ during a control interval is influenced by both water draw and heating element operation. The following equation is derived from the physics of the water heater model to estimate the next time step (hourly or 5-minute interval) $SOHE$ for formulating the agent control. The $SOHE$ at the end of the interval Δt can be characterized as follows:

$$\Delta\, SOHE_{0-1} = c_0 + c_1 \left(E_{Upper} + E_{Lower} - Q_{Draw}\right) + c_2\, SOHE_0 \tag{4-12}$$

Where:

$$c_o = \frac{UA\,\Delta t\, SOHE_{Amb}}{\left(\frac{UA\Delta t}{2} + \rho\, Cp\, V_{Tank}\right)} \tag{4-13}$$

$$c_1 = \frac{1}{\left[\left(\frac{UA\,\Delta t}{2} + \rho\, Cp\, V_{Tank}\right)\left(T_{Desired} - T_{Cold}\right)\right]\left[3413\,\frac{Btu}{kWh}\right]} \tag{4-14}$$

$$C_2 = 1 - \frac{\left(\frac{UA\,\Delta t}{2} - \rho\, Cp\, V_{Tank}\right)}{\left(\frac{UA\,\Delta t}{2} + \rho\, Cp\, V_{Tank}\right)} \tag{4-15}$$

Here the term $SOHE_{Amb}$ is defined with respect to the ambient tank temperature as:

$$SOHE_{Amb} = \frac{(T_{Amb} - T_{Cold})}{(T_{DESIRED} - T_{Cold})} \quad (4\text{-}16)$$

The terms used in equation (4-12) are described below as:

Energy Consumption: The energy consumed by the upper and lower heating elements E_{Up} and E_{LOW}, respectively, [kWh]) is estimated as the product of their respective on times and off times (e.g., On_{Up}/On_{Low}) during each hourly interval in the time series and their power rating P_{rating} at nominal service voltage, e.g., (P_E; 4.5-kW at 240-V):

$$E_{Upper} = On_{Up} \cdot P_{rating} \, [\frac{hr}{60} - min] \quad (4\text{-}17)$$

$$E_{Lower} = On_{Low} \cdot P_{rating} \, [\frac{hr}{60} - min] \quad (4\text{-}18)$$

and the total energy delivered by the heating elements (Q_E in [kWh]) over the hourly interval is simply given as:

$$Q_E = E_{Upper} + E_{Lower} \quad (4\text{-}19)$$

Energy of Hot Water Draw: Let the elapsed time of a *water draw event* (i) be $\Delta t_{draw}(i)$ [min] and the volumetric flow rate during the draw (i) be $\dot{V}_{Draw}(i)$ in gal/min. The total water is drawn $V_{Draw}(i)$ [gal] during an hourly interval with N water draw events is then:

$$V_{Draw}(i) = \sum_{i=1}^{N} \dot{V}_{Draw}(i) \, \Delta t_{draw}(i) \quad (4\text{-}20)$$

Given the assumptions above, the energy of the water withdrawn from the hot water tank Q_{Draw}[1] in [kWh] is independent of the temperature of the hot water and is:

$$Q_{draw} = \rho \, C_p \Delta t_{draw}(T_{Desired} - T_{Cold}) \cdot 7.48 \frac{gal}{ft^3} \cdot \frac{kWh}{3413 \, Btu} \quad (4\text{-}21)$$

Figure 37 shows that the ΔSOHE estimated from the equations above closely matches the actual change in SOHE for the 5-minute interval. Here, ΔSOHE in the y-axis is expressed in terms of ratio and change can be positive or negative.

[1] *Note: Please refer to "Fully-Mixed Water Heater Agent Heat Balance" document written by Rob Pratt for following the derivation of the above equations and modeling. The above equation for ΔSOC model is equation (22) in the document.*

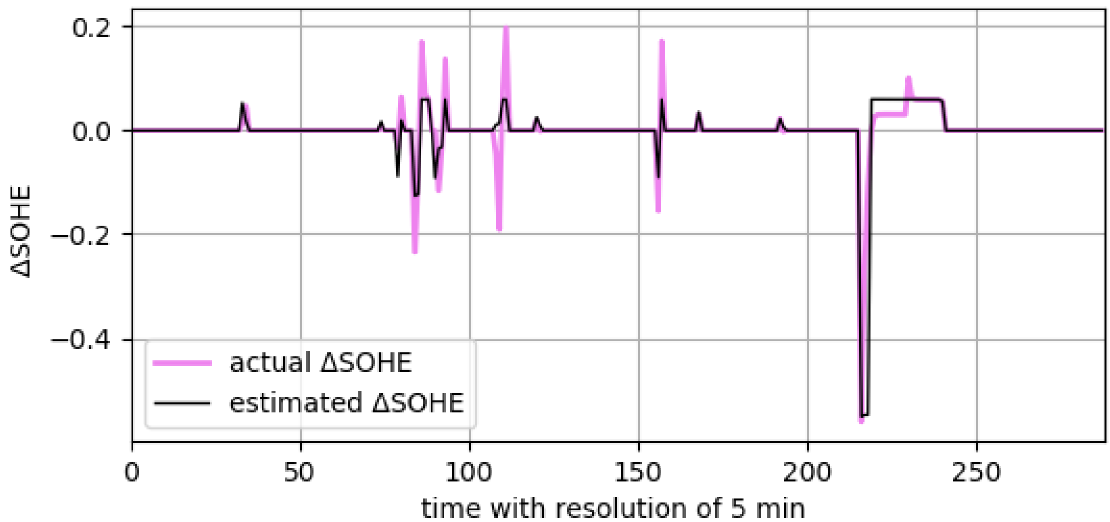


Figure 37. ΔSOHE estimation.

Water Heater Control Strategy: Planning

The equations that predict SOHE are used to develop the operational plan for the water heater. Operational planning process schedules the desired quantity of energy for each hour given the forecast retail price $P(t)$ and forecast water draw schedule $fr_{waterdraw}$. The operational planning process is formulated as a quadratic optimization problem with the objective to minimize the cost of electricity and the cost of user discomfort.

The operational scheduling formulation for objective function and constraints is as follows:

$$\begin{aligned} \underset{E_{upper},E_{Lower}}{\text{maximize}} \sum_{t=1}^{48} \omega * \frac{\left(SOHE_{desired} - SOHE(t)\right)^2}{100} \\ + (1-\omega) \times P \quad (t) \times \left(E_{upper}(t) + E_{Lower}(t)\right) \\ /(P_{rating}) - \beta \times ((E_{upper}(t) + E_{Lower}(t))/P_{rating})^2 \end{aligned} \tag{4-22}$$

Subject to:

$$0 < E_{Upper}(t) < P_{rating} \times 1 \; \forall t \in T \tag{4-23}$$

$$0 < E_{Lower}(t) < P_{rating} \times 1 \; \forall t \in T \tag{4-24}$$

$$0 < E_{upper}(t) + E_{Lower}(t) < P_{rating} \times 1 \; \forall t \in T \tag{4-25}$$

$$\begin{aligned} SOHE(t+1) = SOHE(t) + co0 + co1 \times (E_{upper}(t) + E_{Lower}(t) - Q_{draw}(t)) \\ + co2 \times SOHE(t) \; \forall t \in T - \{N\} \end{aligned} \tag{4-26}$$

$$Q_{draw}(t) = \rho \times C_p \times fr_{waterdraw}(t) \times (T_{desired} - T_{cold}) \; \forall t \in T \tag{4-27}$$

$$SOHE_{min} < SOHE(t) < SOHE_{max} \quad \forall t \in T \tag{4-28}$$

A slider setting ω is introduced to leverage the importance of user comfort and cost saving. The higher the value ω is, the more important the user comfort is treated against cost saving. This slider setting is consistent with the concept introduced in generic agent design in Section 4.2.2.1, where a water heater with a slider setting of ‘1’ provides maximum flexibility, whereas with a slider setting of ‘0’ it prioritizes comfort irrespective of the electricity price. An example of hourly operations scheduling can be seen in Figure 38.

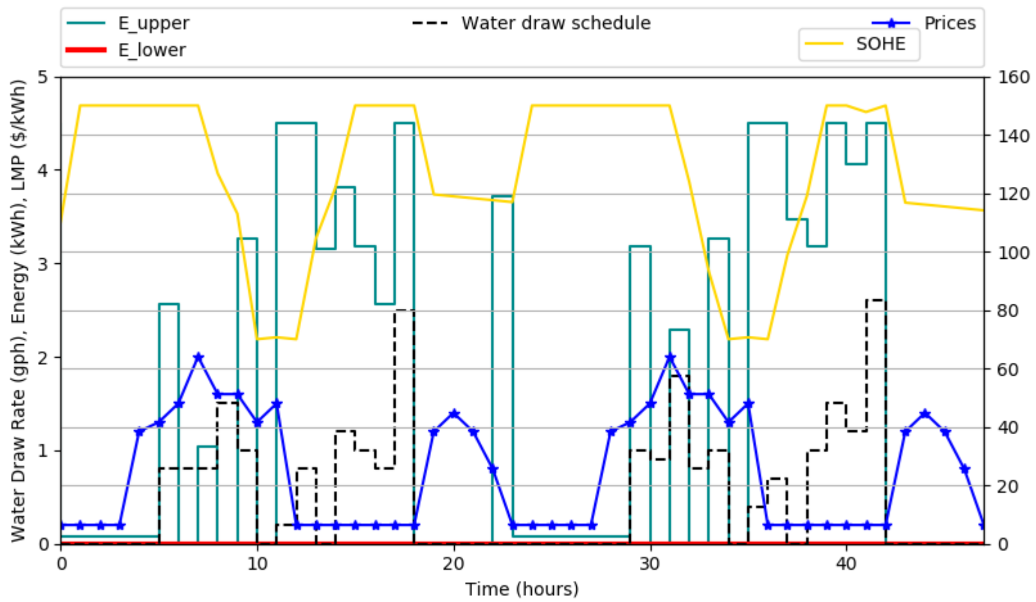


Figure 38. Example of water heater operations scheduling.

Figure 38 shows that the energy consumed by the water heater is lower when the prices are high and heats up when the prices are low. It also shows that the energy consumed follows the water draw pattern and the SOC reflects the heat content in the water heater tank.

To make sure that the physics of the water heater model is estimated accurately, model validation is performed by whether the asset agent model consumed the same amount of energy as the GridLAB-D model with the same temperature setpoints followed and identical physical parameters. A single day-ahead optimization is performed and the resulting quantities are converted to the required temperature setpoints. These setpoints are input into GridLAB-D to obtain the energy consumed by the water heater model in GridLAB-D.

Figure 39 shows the energy consumed by the agent model is following the GridLAB-D water heater. The average energy consumed by the agent model in a day is 0.44375 kWh and the average energy consumed by the water heater in GridLAB-D is 0.45255 kWh in a day. The values match closely (within 2%), hence we can verify that the agent model estimated the physics well enough for the control of the water heater.

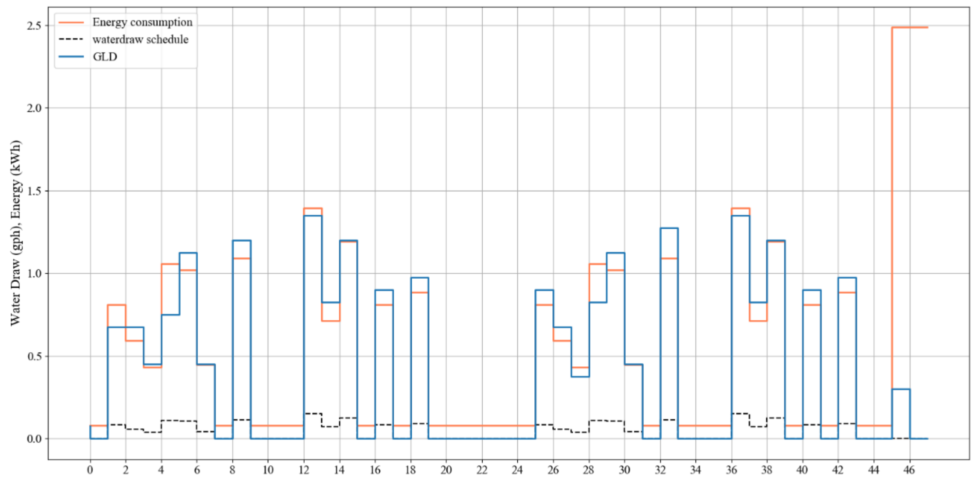


Figure 39. Comparison of energy consumption from GridLAB-D with agent model.

Water Heater Control Strategy: Market Participation

Water heater agent participates in retail day-ahead and real-time markets. To achieve cost-efficient operation, water heater agents bid in the day-ahead market following the guidance of estimated retail day-ahead prices. Intuitively, they are encouraged to bid a higher quantity when the market price goes down and bid a lower quantity when the price goes up. A day-ahead bidding process is iterated every hour in the retail market. This allows the asset agents to revise their bids given updated estimation of prices and changes in the operations schedule. The hourly iterations mitigate market price volatility issues and normalize price expectations to improve real-time market participation. In between these day-ahead intervals, the water heater agent participates in the real-time market that runs every 5 minutes.

Day-Ahead Market Participation

The day-ahead market participation involves a two-step process, namely quantity optimization and bid curve formulation. The day-ahead operations schedule is done based on the formulation presented in Equation (4-22). After the bid quantities are obtained from day-ahead scheduling, a four-point bidding curve is constructed as shown in Figure 40.

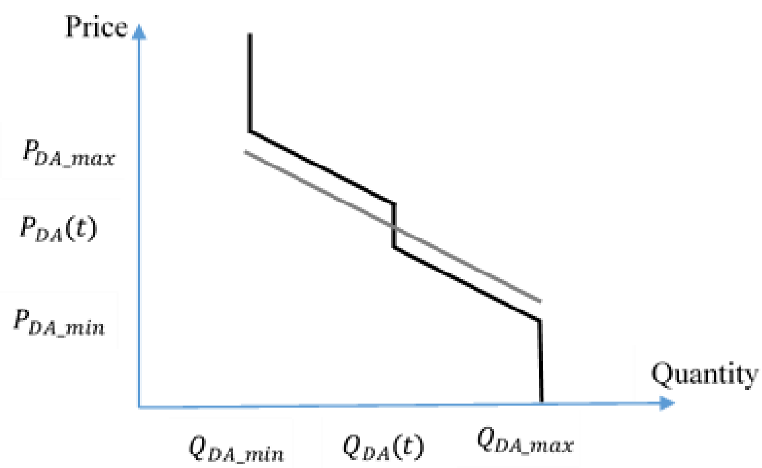


Figure 40. Day-ahead four-point bidding curve.

Given the range of estimated retail prices for the next 48 hours and valid bid quantity, the slope of the line connecting point (Q_{DA_min},P_{DA_max}) and point (Q_{DA_max},P_{DA_min}) in Figure 40 can be calculated, denoted here as ρ.

$$\rho = \frac{P_{DA\_max} - P_{DA\_min}}{Q_{DA\_max} - Q_{DA\_min}} \times \left(1 + \frac{PM - S}{100}\right), \tag{4-29}$$

with

$$yIntercept = P_{DA}(t) - \rho(t) \cdot Q_{plan} \tag{4-30}$$

Once the value of $P_{DA}(t)$ and $Q_{opt}(t)$ are fixed, the four-point curve can be uniquely determined based on the values of ρ and $yIntercept$, so that the slope of the bidding curve remains as ρ.

$$\Delta f_{DA} = P_{DA\_max} - P_{DA\_min} \tag{4-31}$$

The four-point curve can be calculated as follows, each (P1, Q1) pair is one of the points in the bid curve.

Quantity:

$$P1_q = 0 \tag{4-32}$$

$$P2_q = Q_{plan} \tag{4-33}$$

$$P3_q = Q_{plan} \tag{4-34}$$

$$P4_q = P_{rating} \tag{4-35}$$

Price:

$$P1_p = \rho + yIntercept + \frac{PM - I}{100} \times \Delta f_{DA} \tag{4-36}$$

$$P2_p = Q_{plan} \times \rho + yIntercept + \frac{PM - I}{100} \times \Delta f_{DA} \tag{4-37}$$

$$P3_p = Q_{plan} \times \rho + yIntercept - \frac{PM - I}{100} \times \Delta f_{DA} \tag{4-38}$$

$$P4_p = Q_{rate} \times \rho + yIntercept - \frac{PM - I}{100} \times \Delta f_{DA} \tag{4-39}$$

Real-Time Market Participation

Due to the intrinsic uncertainties existing in the system, the real-time operation deviates from the day-ahead schedule. The real-time market process is used by the asset agent to make adjustments in response to the conditions. Bids are submitted every 5 minutes. The upper quantity bound Q_{RT_max} and lower quantity bound Q_{RT_min} of the real-time bid curves vary across time and need to be adjusted based on the updated device status. The same process is applied to the upper price bound P_{RT_max} and lower price bound P_{RT_min} based on the latest price-trend estimation.

During real-time operation, the asset agent updates its knowledge of the water heater thermostat on/off state and thermostat temperatures from GridLAB-D every 5 minutes. This updates the energy consumption based on both thermostats and SOHE of the tank.

The day-ahead scheduled quantity and price obtained from operations scheduling are directly used for the real-time bid curve formulation, but the upper quantity bound Q_{RT_max} and lower quantity bound Q_{RT_min} are both corrected for real-time operation according to the device status for achievable control within the 5-minute window.

Based on the near-real-time SOHE status, the water heater agent falls into five different scenarios, where scenarios 1, 2, and 3 help determine the Q_{RT_max} and scenarios 1, 4, and 5 help determine the Q_{RT_min}. Figure 41 illustrates the scenarios a) when water heater bids its full capacity Q_{RT_min}=Q_{RT_max}, b) when $\boldsymbol{Q_{DA}}\ (\boldsymbol{t})/\mathbf{12} < \boldsymbol{Q_{RT\_min}}$ or $\boldsymbol{Q_{DA}}\ (\boldsymbol{t})/\mathbf{12}\ > \boldsymbol{Q_{RT\_max}}$, and c) when $\boldsymbol{Q_{DA}}\ (\boldsymbol{t})/\mathbf{12}$ lies within $[\boldsymbol{Q_{RT\_min}}, \boldsymbol{Q_{RT\_max}}]$.

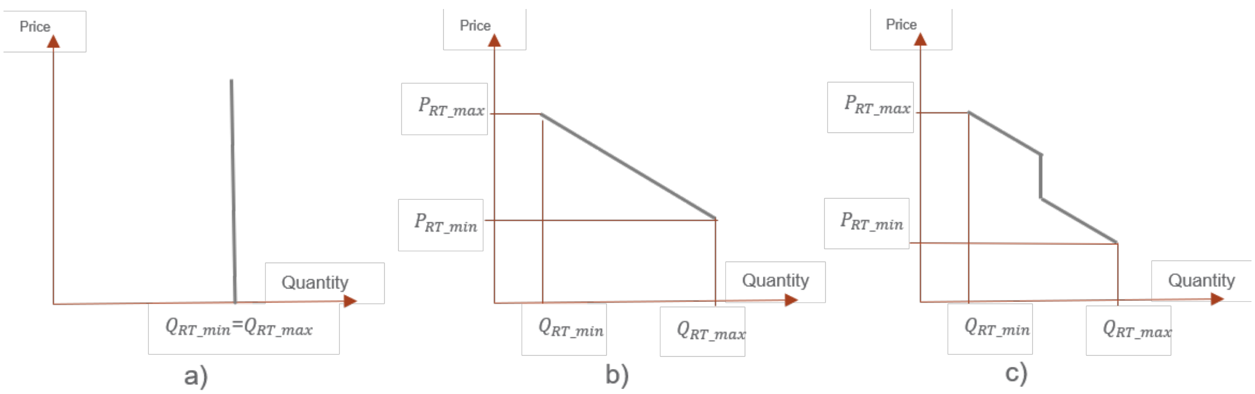


Figure 41. Real-time market mapping from scenarios.

Scenario 1: Current SOHE being lower than the $SOHE_{min}$ (due to inappropriate device operation or heavy water draw happening in the previous time steps).

In this case, the water heater agent will bid the full capacity (i.e., always on).

$$Q_{RT\_max} = Q_{RT\_min} = P_{rating}/12 \tag{4-40}$$

And when the current SOHE is higher than the $SOHE_{max}$, then the water heater agent will bid zero quantity.

$$Q_{RT\_max} = Q_{RT\_min} = 0 \tag{4-41}$$

Scenario 2: The SOHE falls in the range of [$SOHE_{min}$, $SOHEC_{max}$]; however, running the heating element at its full capacity for the next 5 minutes will make SOHE exceed SOC_{max}.

In this case, the upper quantity bound should be the quantity that necessarily heats the SOC to reach SOC_{max}. Such quantity can be estimated using ΔSOC estimation model and is bounded by the heating element maximum output.

$$Q_{RT\_max} = \max\Big(\big(SOC_{max} - SOHC(t)\big) - c_0 + c_1 \times Q_{draw}(t) \\ - c_2 \times SOHC(t)/c_1, P_{rating}/12\Big)$$

Scenario 3: The SOC falls in the range of [SOC_{min}, SOC_{max}] and running the heating element on its full capacity for the next 5 minutes will not make the SOC exceed SOC_{max}. In this case, the upper quantity bound is the full capacity of the water heater,

$$Q_{RT\_max} = P_{rating}/12. \tag{4-42}$$

Scenario 4: The current SOC is in the range of [SOC_{min}, SOC_{max}]; however, these will go below SOC_{min} if both heating elements are turned off during the next 5 minutes. In this case, the lower quantity bound should be the quantity that necessarily maintains the SOC not to below SOC_{min}.

$$Q_{RT\_min} = \max\Big(\big(SOC_{min} - SOHC(t)\big) - c_0 + c_1 \times Q_{draw}(t) - c_2 \times SOHC(t)/c_1, P_{rating}/12\Big) \tag{4-43}$$

Scenario 5: The current SOC is in the range of [SOC_{min}, SOC_{max}]; however, these will not go below SOC_{min} if both heating elements are turned off during the next 5 minutes. In this case, the lower quantity bound is zero.

$$Q_{RT\_min} = 0 \tag{4-44}$$

The day-ahead scheduled quantity and price obtained from the operational scheduling is directly used for real-time bid curve formulation. The value of day-ahead hourly schedule and hourly forecast prices are used to formulate real-time bids every 5 minutes. Because discontinuities could appear at the hourly boundary if the same value is used for every 5-minute interval for an hour, the smoothing interpolation method of using day-ahead prices in Figure 25 is applied here as well. The translation of day-ahead planned quantities into real-time bids using the rules described above are summarized in Section 4.2.2.1.

Market Control Mapping

The water heater asset agent is responsible for the real-time control of the water heater model. After being informed with the real-time cleared price each 5 minutes, the water heater agent needs to map the cleared price into an actuation signal to be sent to the physical water heater. The water heater agent sends the corresponding actuation signal to the water heater to guide its operation. The water heater is controlled via two heating element thermostats, with actuation priority on the upper one. S_{upper} and S_{bottom} denote the setpoints of each element. The upper and bottom heating elements track S_{upper} and S_{bottom} respectively to maintain the temperature to be inside the control deadband (within $\pm 1°\text{F}$ of the setpoint). The SOHE-to-quantity approximation presented in Figure 42 is used to calculate the setpoints.

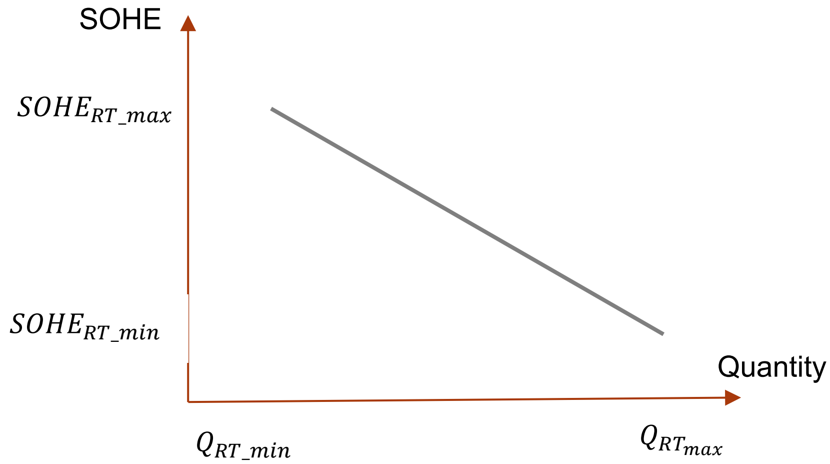


Figure 42. Real-time control based on quantity and SOHE approximation.

Given the cleared quantity $Q_{RT\_cleared}$ and minimum Q_{RT_min} and maximum Q_{RT_min} real-time quantity obtained from the method described in the previous section, the following equation is used to update the $SOHE_{RT\_setpoint}$ setpoints for every 5 minutes.

$$SOHE_{RT\_setpoint} = SOHE_{RT\_min} + \left(Q_{RT_{cleared}} - Q_{RT\_min}\right) \cdot \frac{SOHE_{RT\_max} - SOHE_{RT\_min}}{Q_{RT_{max}} - Q_{RT\_min}} \tag{4-45}$$

Based on this setpoint, the upper and lower setpoints in terms of temperature values are calculated as follows:

- For the case when real-time $SOHE_{RT\_setpoint} < SOHE_{RT\_min}$, (i.e., the approximated SOHE is less than the theoretical SOHE limit) the setpoint is increased to bring the water heater to its acceptable temperature range:

$$S_{upper} = S_{bottom} = T_{max} \tag{4-46}$$

- For the case where the approximated SOHE goes beyond the maximum limit $SOHE_{RT\_setpoint} > SOHE_{RT\_max}$, the temperature setpoints are reduced to bring the water heater to its acceptable range:

$$S_{upper} = S_{bottom} = T_{min} \tag{4-47}$$

- When $SOHE_{RT\_min} \leq SOHE_{RT_{setpoint}} \leq SOHE_{RT\_max}$, then a linear approximation is used to arrive at the setpoints:

$$S_{upper} = S_{bottom} = [SOHE_{RT\_setpoint} * (T_{Desired} - T_{cold})] + T_{cold} \tag{4-48}$$

Figure 43 shows the temperature setpoints given to the GridLAB-D water heater model and the upper and lower tank temperatures are following the setpoints. To demonstrate the independent control of upper and lower heating elements, the upper and lower tank setpoints are scheduled to follow the upper and lower limits of temperature requirements. The lower thermostat temperature follows the setpoints dynamically, whereas the upper has a delayed response but follows the trend of the temperature setpoints. This delay emulates the thermal inertia of the tank, as the cold water, due to water draws, causes the lower part of the tank to get cooled and then stratified layers introduce delays of this heat to reach the top of the tank.

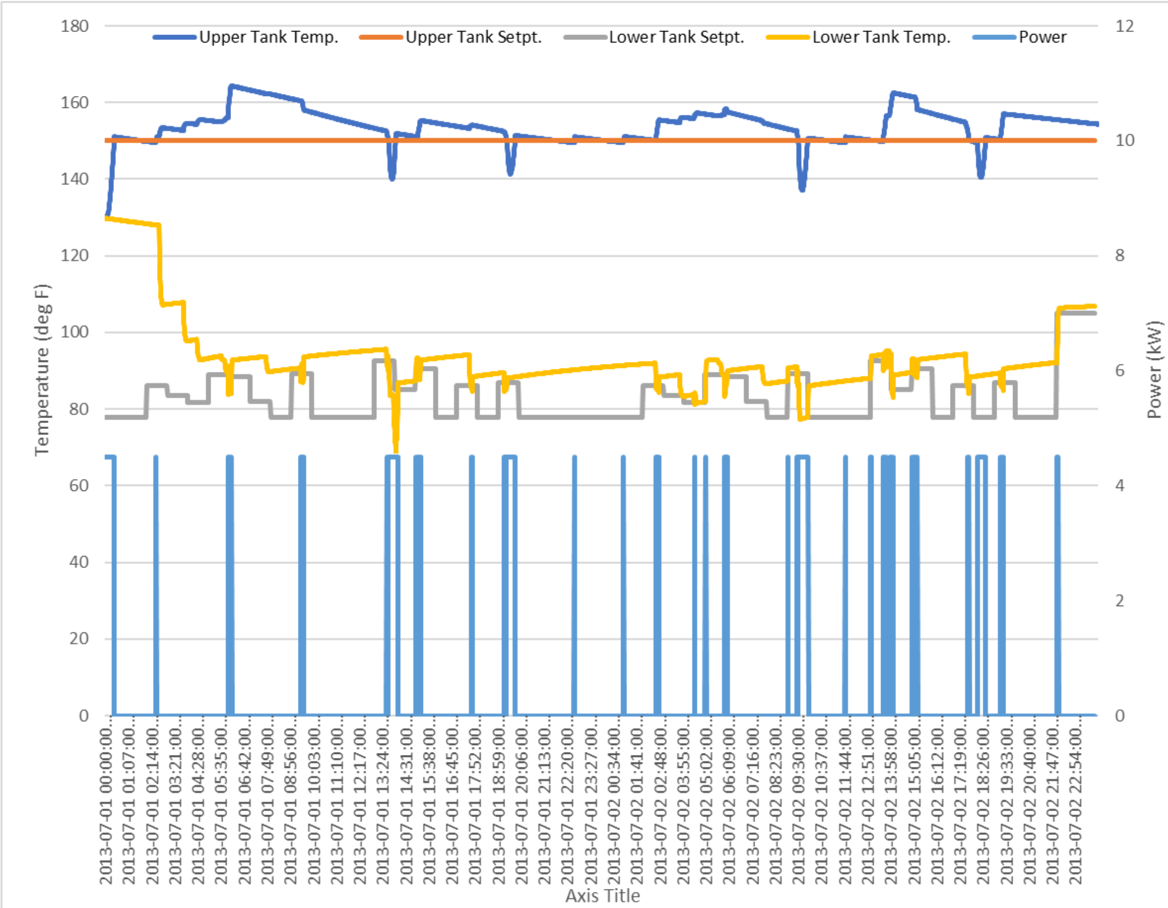


Figure 43. Real-time control of temperature setpoints; apart from temperature setpoints, the power draw is also influenced by the water draw schedule.

4.2.2.4 Battery Transactive Agent Design

The battery asset agent is responsible for generating price-quantity bids for participating customer submission to the day-ahead and real-time retail markets. The battery agent provides the flexibility to alter the battery's charging and discharging quantities and times in relation to the retail price. The battery agent is responsible for supervisory control of the battery equipment and retail market participation.

The day-ahead bids are based on the expected plan of action for the next 48 hours. This is used as a baseline for the real-time retail market participation, i.e., its behavior. Market participation occurs every 5 minutes and every 5 minutes the agent interacts with the battery and inverter, reading the battery SOC, and adjusting the inverter power settings. With updates of local information and its day-ahead plan, the agent generates bids that attempt to follow its plan, considering the battery limitations. Once the real-time retail market clears, the price the agent converts that information to controls the inverter.

Battery Agent Model

The agent perceives the battery as charging and discharging energy from stored energy C^{init} and with linear charging and discharging losses L^{in} and L^{out}. Thus, for discharging:

$$C_{exp}^{init} = C^{init} - set\ inverter\ power \times \left(1 - \frac{L^{out}}{100}\right) \times time \tag{4-49}$$

where C_{exp}^{init} is the expected available store energy after the given time. Equivalently for charging:

$$C_{exp}^{init} = C^{init} + set\ inverter\ power \div \left(1 - \frac{L^{in}}{100}\right) \times time \tag{4-50}$$

For the battery agent to participate in the day-ahead and real-time markets, it uses a model of the battery and the inverter. Once the battery agent is instantiated, it receives the characteristics of the inverter and battery being controlled. The list of the initialization parameters that remain constant through time is presented below:

R^c = Battery rated charging energy in kWh

R^d = Battery rated discharging energy in kWh

L^{in} = Battery charging loss in percentage

L^{out} = Battery discharging loss in percentage

C^{min} = Battery minimum stored energy allowed (SOC lower limit) in kWh

φ = Constant to model battery degradation in \$/kWh

B^S = Spread bids by reducing R^c and R^d, if set to 1 hour (recommended) the effect is none

DA^c = Percentage of battery capacity to be bid day-ahead

ω = Slider (unitless)

PM = Profit margin, i.e., battery bid slider setting, unitless

RT^{sm} = Set battery to maintain state, i.e., if true the battery must maintain charging or discharge for 1 hour, true or false.

Battery Scheduling

The battery can store energy (C) and maximum (C^{max}) and minimum (C^{min}) allowable amount of energy in kWh. The energy stored in the battery can be altered by the inverter given its combined limitations of maximum charging (R^c) and discharging (R^d) rate in kW. The process of charging and discharging the battery contains the losses of the inverter and the battery. The losses are considered charging losses (L^{in}) and discharging losses (L^{out}) in percentage. The battery model also considers the battery life degradation factor (φ) in \$/kWh to avoid being overused. The agent day-ahead bidding considers these characteristics to optimize the quantity being charged or discharged in real time given the forecast of the retail market price.

The external input parameters required are the battery characteristics and forecast day-ahead electricity prices. Battery characteristics are unique to each battery, whereas the forecast electricity price could be the same for all batteries (if subscribed from the same source) or different (if subscribed from different sources). Based on the forecast price and battery characteristics, each battery makes operational schedules for a given window length (N), where $T = \{1,2, \ldots, N\}$, and $T_2 = \{2,3, \ldots, N\}$.

The optimization formulation for scheduling, published in (Bhattarai et al. 2020a), is as follows:

Notation:

$E_{DA}^{out}(t)$ = Discharge bid, hour t, in kWh

$E_{DA}^{in}(t)$ = Charge bid, hour t, in kWh

$E_{stor}^{in}(t)$ = Energy into the storage, hour t, in kWh

$E_{stor}^{out}(t)$ = Energy out of the storage, hour t, in kWh

$C(t)$ = Stored energy in the battery, hour t, in kWh

The objective function and constraints:

$$\underset{E_{DA}^{out}, E_{DA}^{in}}{\text{maximize}} \sum_{t \in T} \left[P(t). \left(E_{DA}^{out}(t) - E_{DA}^{in}(t) \right) - \varphi. \left(E_{DA}^{out}(t) + E_{DA}^{in}(t) \right) - \beta \left(E_{DA}^{out}(t) + E_{DA}^{in}(t) \right)^2 \right] \quad (4\text{-}51)$$

Subject to:

$$E_{DA}^{out}(t) \geq 0 \ \forall t \in T \quad (4\text{-}52)$$

$$E_{DA}^{in}(t) \geq 0 \ \forall t \in T \quad (4\text{-}53)$$

$$0 \leq E_{stor}^{out}(t) \leq R^d \ \ \forall t \in T \quad (4\text{-}54)$$

$$0 \leq E_{stor}^{in}(t) \leq R^c \ \ \forall t \in T \quad (4\text{-}55)$$

$$C^{min} \leq C(t) \leq C^{max} \ \ \forall t \in T \quad (4\text{-}56)$$

$$E_{stor}^{in}(t) \leq \frac{DA^c}{100} \times \frac{R^c}{B^S} \ \ \forall t \in T \quad (4\text{-}57)$$

$$E_{stor}^{out}(t) \leq \frac{DA^c}{100} \times \frac{R^d}{B^S} \ \ \forall t \in T \quad (4\text{-}58)$$

$$E_{DA}^{in}(t) = E_{stor}^{in}(t) \div \left(1 - \frac{L^{in}}{100} \right) \ \ \forall t \in T \quad (4\text{-}59)$$

$$E_{DA}^{out}(t) = E_{stor}^{out}(t) \times \left(1 - \frac{L^{out}}{100} \right) \ \ \forall t \in T \quad (4\text{-}60)$$

$$C(1) = C^{init} - E_{stor}^{out}(1) + E_{stor}^{in}(1) \quad (4\text{-}61)$$

$$C(t) = C(t-1) - E_{stor}^{out}(t) + E_{stor}^{in}(t) \ \forall t \in T_2 \quad (4\text{-}62)$$

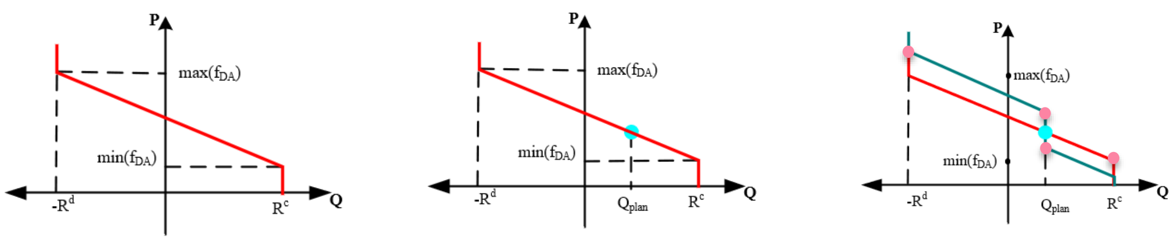
The output of the optimization provides the operational schedules that provide maximum profit for the battery agent. For the solution of the optimization problem, the forecast of the day-ahead retail price should be near the cleared price after the agent's bids. Furthermore, the behavior of the battery's real-time (expected SOC at every hour) is assumed to follow the operational plan.

Battery Market Participation

A battery asset agent's cost-efficient operation is dependent on market behavior. The battery agent bids following the guidance of forecast day-ahead retail market prices. Intuitively, the agent is encouraged to bid a higher charging quantity during the low retail market price and bid a higher discharging quantity for high retail market price. In order to deal with the price volatility and deviations from the day-ahead plan, such a bidding process is iterated every hour in the retail market by allowing battery agents to rebid considering updated estimates of local state (battery SOC) and system expected behavior (new forecast retail prices).

Battery Day-Ahead Market Participation

To generate the four-point battery agent bid curve requires knowledge of the planned operating quantity for a given hour ($Q_{plan}(t)$), profit margin (PM). The four points are computed as shown in Figure 44. Figure 44(a) presents the initial curve with the maximum charging and discharging limits with respect to the maximum and minimum forecast price. The physical limitations are reflected in the bid curve by introducing vertical lines at the max charging/discharging limits as shown in Figure 44(b). The PM increases the profit margin required for a change in quantity. With the consideration of PM results in the Figure 44(c) having the four points represented as purple circles.



(a) (b) (c)

Figure 44. Conceptual illustration of significance of the day-ahead four-point bidding.

For every hour, the slope of the curve is computed with

$$C_{slope} = \frac{\max(P(t)) - \min(P(t))}{-R^d - R^c} \div \omega \tag{4-63}$$

the intercept to compute with

$$C_{intercept}(t) = P(t) - C_{slope} \times Q_{plan}(t) \tag{4-64}$$

points are computed with

$$\begin{cases} P1_p(t) = -R^d \times C_{slope} + C_{intercept}(t) + \varphi \times (1 + \mathrm{PM}) \\ P1_q = -R^d \end{cases} \tag{4-65}$$

$$\begin{cases} P2_p(t) = Q_{plan} \times C_{slope} + C_{intercept}(t) + \varphi \times (1 + \mathrm{PM}) \\ P2_q(t) = Q_{plan}(t) \end{cases} \tag{4-66}$$

$$\begin{cases} P3_p(t) = Q_{plan} \times C_{slope} + C_{intercept}(t) - \varphi \times (1 + \mathrm{PM}) \\ P3_q(t) = Q_{plan}(t) \end{cases} \tag{4-67}$$

$$\begin{cases} P4_p(t) = -R^c \times C_{slope} + C_{intercept}(t) - \varphi \times (1 + \mathrm{PM}) \\ P4_q = R^c \end{cases} \quad (4\text{-}68)$$

Where $P(.)_p$ price at $(.)$, $P(.)_Q$ quantity at $(.)$, and $(.)$ is the number of the point, from 1 to 4.

Battery Real-Time Market Participation

Due to the intrinsic uncertainties existing in the system, real-time operation deviates from the day-ahead; therefore, the real-time retail market performs the adjustments for the deviations. Unlike the day-ahead bidding, real-time bidding is submitted every 5 minutes. The battery agent participation is performed by considering the battery's physical limitations and day-ahead plan. The real-time operation updates its knowledge of the battery's SOC every 5 minutes, thus updating the battery initial stored energy (C^{init}). The real-time bid curve formulation uses the day-ahead bid by changing the quantity-bid range depending on the SOC. The linear interpolation of the retail day-ahead market-cleared quantity as illustrated in Figure 25 is used to smooth the transition over the day-ahead hour boundary.

On initialization, the agent can be configured to maintain its battery state (charging and discharging) over the duration of 1 hour. Thus, real-time bids are also affected by the selection of battery state maintenance.

Market Control Mapping

The battery agent exchanges information with GridLAB-D twice at every 5 minutes; first to update the agent's knowledge of the battery SOC and second to set the inverter power once the real-time market has been cleared. The received SOC is subject to

$$C^{min} \leq C^{max} \times SOC \leq C^{max} \quad (4\text{-}69)$$

where, C^{min}, C^{max}, and C^{init} are the battery minimum, maximum, and initial/current stored energy (in kWh) respectively. Thus, the computed currently available stored energy or C^{init} is always made to be within its upper and lower boundary. The unit of SOC is in (p.u.) having a range of 0 to 1.

Once the cleared real-time retail price is returned to the asset agent, its submitted bid is used to compute the inverter power settings ($set\ inverter\ power$ (in W)). The submitted real-time bid quantity range considers the inverter limitations, i.e.,

$$-R^d \leq set\ inverter\ power \leq R^c \quad (4\text{-}70)$$

where, $-R^d$ and R^c are the inverter rated charging and discharging, respectively (in kW), thus setting the state and quantity of the battery to charging, discharging, or idle (power equal to zero).

Battery Degradation Cost

The participation of the battery in a transactive marketplace is driven by the cost to furnish one full cycle as

$$Cost\ per\ Cycle = \left(\frac{1}{\eta} - 1\right)(LMP_{low} + D_{dc}) + \varphi.(1 + Profit) \tag{4-71}$$

where the first term represents the cost of the battery inefficiency that is made up of the losses due to round-trip efficiency (η) and retail rate of the electricity. ($LMP_{low} + D_{dc}$) is the average retail price of electricity when the battery is charged. The second term represents the capital cost for one cycle and comprises the battery degradation cost per cycle (φ), and $Profit$ that is the expected profit over the life of the battery. For this analysis, it is assumed that the battery degradation cost is dominated by cyclic degradation and not by calendar degradation. Furthermore, while the cycle degradation rate is a function of cycle depth, for this work we assume a simple linear relationship and not a piecewise linear model. This relationship is first-order accurate by Xu et al. (2018). Therefore, the degradation cost can be stated as:

$$\varphi = \frac{First\ Cost}{Cycles} \tag{4-72}$$

Where the $First\ Cost$ is the cost of the total system to be replaced or refurbished at the end of its life (including installation) and $Cycles$ represent the total number of cycles that can be operated over a battery lifetime.

For the battery agent to participate in a transactive energy marketplace the cost per cycle needs to be less than or equal to the retail price variation seen during the 48-hour optimization horizon. Therefore:

$$\begin{aligned}(LMP_{high} + D_{dc}) - (LMP_{low} + D_{dc}) \\ = \left(\frac{1}{\eta} - 1\right)(LMP_{low} + D_{dc}) + \varphi.(1 + Profit)\end{aligned} \tag{4-73}$$

Given the above, the $First\ Cost$ required for the battery to participate in a transactive marketplace can be stated as

$$First\ Cost = \frac{\left((LMP_{high} + D_{dc}) - \frac{1}{\eta}(LMP_{low} + D_{dc})\right) cycles}{(1 + profit)} \tag{4-74}$$

Assuming a 12% profit and a daily high LMP of \$0.04/kWh and low of \$0.01kWh, and a distribution cost of \$0.03/kWh, the calculated first cost is \$83/kWh. As shown in Table 3, with 3,659 lifetime cycles, the battery cycle degradation cost (ϕ) turns out to be 0.02274 \$/kWh round trip. Note that the LMPs used in this example are representative of median daily high and low LMPs based on ERCOT 2016 data.

Table 3. Example battery operational costing characteristics.

Battery cycle degradation cost (φ, \$/kWh round trip)	0.02274
Lifetime cycles (n)	3,650
Installed system first cost (\$/kWh)	83
Profit (%)	12

Note that this represents the first cost target needed to participate in a transactive marketplace. This analysis does not consider other services (such as frequency regulation) and value propositions (such as backup power for resiliency). Such value propositions, assuming they could be stacked, would increase the acceptable first cost of the battery.

4.2.2.5 Electric Vehicle Transactive Agent Design

A transactive electric vehicle (TEV) asset agent is designed to enable the utilization of EV flexibility for utility and customer benefits. A high-level operational framework for the TEV agent is illustrated in Figure 45. The TEV agent is designed as a supervisory controller for the actual EV that involves the following four core functionalities: EV model estimation, optimum scheduling, market bidding mechanism, and control implementation. The following subsections detail each of the functions of the TEV.

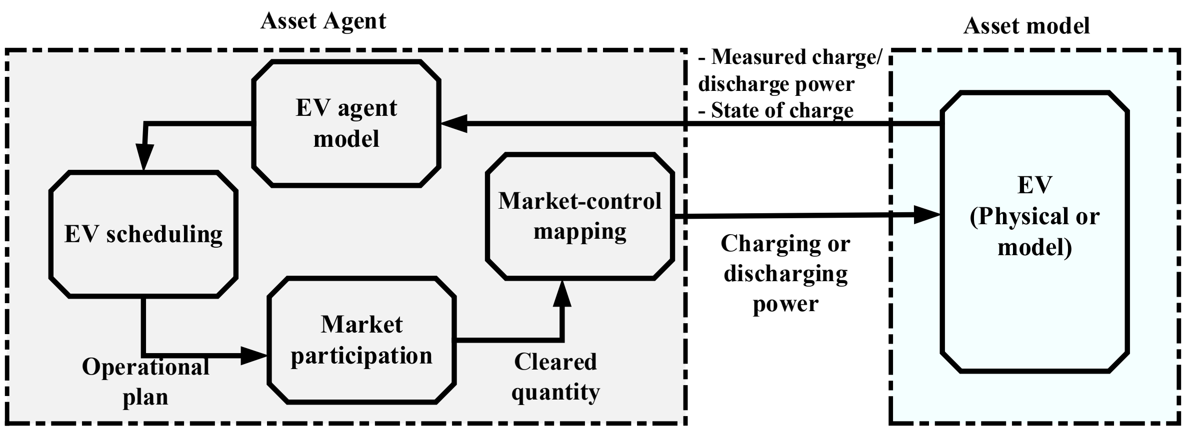


Figure 45. Schematic diagram of EV agent interaction with EV asset.

EV Model Estimation

The model estimation module estimates the physical behavior and operational parameters of the EV. The EV asset agent monitors certain parameters directly from the EV (physical or device simulation model) and uses those parameters for estimating the dynamics of the EV. In particular, the module estimates SOC, charging/discharging power quantities, and travel efficiency. The agent module also estimates properties such as plug-in/plug-out time and estimated travel time. The detailed EV modeling is discussed in Vol. 2, Section 10 (Reeve, Singhal, et al. 2022a). The parameters that remain the same each day for a given EV for a given simulation are listed in Table 4.

Table 4. EV parameter list

Plug-in time	t_{in}	The latest time the car arrives home
Plug-out time	t_{out}	The earliest time the car leaves home
Plug-in duration	T_p	Time elapsed between t_{in} and t_{out}
Miles traveled	d	Daily total miles are driven by the car
Range (miles)	r	Maximum miles the EV can drive per one full charge cycle
Mileage efficiency	m	Discharge rate while driving, given in miles/kWh
Charging rating (kWh)	E_{max}^{in}	Maximum energy a charger can transfer from grid to EV in 1 hour
Discharging rating (kWh)	E_{max}^{out}	Maximum power a charger can transfer from EV to grid in 1 hour
Charging efficiency	η_{in}	Conversion ratio of the energy addition in EV to the energy input from the grid in V1G mode
Discharging efficiency	η_{out}	The conversion ratio of energy transferred to the grid to the energy depletion in EV in V2G mode

EV Scheduling

The optimization module prepares an optimal operational schedule for the EV. The schedules are prepared based on the forecast electricity prices and the EV model estimation (e.g., EV dynamic behavior, plug-in/plug-out time, estimated travel time, EV battery efficiency). The optimization module also includes user-defined constraints to meet specific needs. For instance, if the user anticipates a long drive on the following day, the user may prefer to set the EV to be fully charged by the start time. The detailed optimization formulation is discussed below.

Modeling Customer's Transactive Preference

To incorporate a retail customer's willingness to participate in the transactive market, we introduce the concept of a slider, ω, that each customer can set to their preferred value on the scale of 0 to 1 as explained in Section 4.2.2.1. A higher ω means the customer is willing to trade their amenity for economic gain in the transactive market. Similarly, a lower ω reflects that the customer values their amenity more than cost savings. In the case of an EV agent, we qualitatively define the customer's amenity as "*availability of a fully charged EV at all times as much as possible,"* whereas savings come from the reduction in the EV charging cost by deferring charging to the lower price intervals. For the purpose of modeling, we can say that the maximum amenity case (i.e., $\omega = 0$) prefers EV to get charged as soon and as fast as possible after arriving home, and requires a fully charged EV before leaving home. Similarly, the maximum profit case (i.e., $\omega = 1$) prefers to minimize cost while charging as long as enough charge is available to cover the daily travel miles before leaving home. Figure 46 illustrates these two scenarios to explain the impact of $\omega = 0$ (max amenity) and $\omega = 1$ (max savings). We will develop the mathematical model of this tradeoff in the next section.

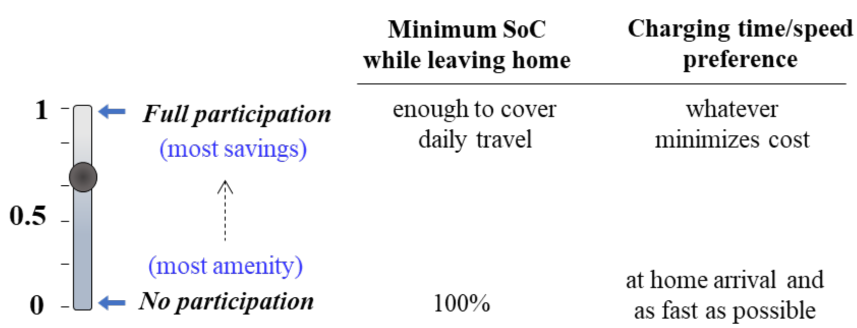


Figure 46. Illustration of how preference slider acts in extreme cases.

Mathematical Formulation

The optimization problem is formulated for each TEV agent separately using its battery characteristics and forecast day-ahead retail price $P(t)$ for the duration T over the next N market intervals (usually hours), where $T = \{1,2, \ldots, N\}$. Define sets $T_{in} \subset T, T_{out} \subset T$ as collections of home arrival and home departure hours, respectively. Further, consider $T_{tran} \subset T$, a set of all hours for which an EV is plugged in.

Based on the discussion in the last section, operational cost of TEV can be defined as

$$Cost = \omega \sum_{t \in T} P(t)\left(E^{in}(t) - E^{out}(t)\right) + \phi\left(E^{out}(t) + E^{in}(t)\right)$$
$$+(1-\omega) \sum_{t \in T_{tran}} \alpha\left(C^{max} - C(t)\right) \quad (4\text{-}75)$$
$$-\beta\left(E^{out}(t) + E^{in}(t)\right)^2$$

where, the first term represents the cost incurred due to charging and discharging the vehicle while accounting for the battery degradation as well. E^{in} and E^{out} are the charging and discharging energy bid respectively in kWh. The EV battery degradation cost is modeled as a constant rate ϕ in \$/kWh. The second term represents the *Discomfort* cost, where $C(t)$ and C^{max} are the stored kWh energy in the EV battery at any given time, t, and maximum possible charge respectively. α is a constant to model the customer's discomfort cost in \$/kWh. $T_{in} \subset T$ is a set of all plugged in hours. The third term is a penalty with a convergence constant β that encourages the agent to spread its charging or discharging bid over multiple intervals. This is important as it discourages agents to respond homogeneously to price and thus avoids synchronized behavior such as large spikes or valleys in the net feeder load that can have destabilizing market consequences between market iterations. As the price forecast is not perfect and is impacted by EV market bidding, an enlightened agent should hedge their bids by spreading them to cover a large range of possibilities. The impact of this term is analyzed in the “EV Performance Evaluation” section later.

A complete optimization formulation with constraints can be written as,

$$\underset{E^{out},E^{in}}{\text{minimize}}\ Cost \quad (4\text{-}76)$$

Subject to

$$0 \le E^{out}(t) \le E^{out}_{max} \times \eta_{out}\ \forall t \in T_{tran} \quad (4\text{-}77)$$

$$0 \le E^{in}(t) \le E^{in}_{max} \div \eta_{in}\ \forall t \in T_{tran} \quad (4\text{-}78)$$

$$E^{out}(t) = 0\ \forall\ t \in T - T_{tran} \quad (4\text{-}79)$$

$$E^{in}(t) = 0\ \forall\ t \in T - T_{tran} \quad (4\text{-}80)$$

$$C^{min} \le C(t) \le C^{max}\ \forall t \in T \quad (4\text{-}81)$$

$$C(t) = C(t-1) - \frac{E^{out}(1)}{\eta_{out}} + E^{in}(t) \times \eta_{in}\ \forall t \in T - (T_{in} \cup T_{out}) \quad (4\text{-}82)$$

$$C(t+1) = C(t) - \frac{Q_d}{2}\ \ \forall t\ \in\ T_{in} \cup T_{out} \quad (4\text{-}83)$$

$$C(t-1) \ge C^b\ \ \forall t \in T_{out} \quad (4\text{-}84)$$

Equations (4-77), (4-78), (4-79), and (4-80) are the constraints on the energy bid magnitudes during plugged in and non-plugged in hours respectively. C^{min} and C^{max} in (4-81) denote the minimum and maximum possible stored energy in kWh. We assume that the daily driving charge $Q_d = d/m$ is drained equally at the departure and arrival hours as reflected in (4-83). During plugged in hours, the battery-stored energy is governed by (4-82). The boundary condition is denoted by (4-84) where C^b is the minimum charge an EV must have before leaving home, which is a function of slider ω as follows:

$$C^b = C^{max} - \omega \times (C^{max} - Q_m) \quad (4\text{-}85)$$

where Q_m is the energy required to drive daily miles with some extra margin. Q_m is a boundary condition charge for a fully transactive customer, i.e., $\omega = 1$.

The proposed TEV agent has the capability to support two EV technologies: grid-to-vehicle (V1G) mode and vehicle-to-grid (V2G) mode. In V1G, TEV is restricted to only charge the vehicle from the grid. It is not allowed to bid net export of energy from the vehicle to the grid. Whereas in V2G, TEV can bid both net import and net export of energy subject to the operational constraints of the EV battery. The optimization formulation in the previous section is for V2G mode. To make it compatible with V1G, constraint (4-79) is changed to the following:

$$E^{out}(t) = 0 \ \forall \ t \in T \quad (4\text{-}86)$$

This ensures the export of energy is always 0 in the case of V1G mode. Comparative study of V1G and V2G will be discussed in the "EV Performance Evaluation" section later.

EV Market Participation

The TEV asset agent participates in retail day-ahead and real-time markets. The TEV agent takes the operational schedules as a reference for day-ahead market participation and prepares price-quantity bid curves around the desired operating point. The bid curve is designed such that any difference between the forecast electricity price (that is used to prepare the operational schedule) and actual electricity price (obtained once the market clears) are taken to properly adjust the operation of the EV in real time. To deal with the price volatility and deviations from the day-ahead plan, the bidding process is iterated every hour in the retail market by allowing the DERs to rebid the next 48 hours given the updated forecast of retail day-ahead prices. In between these intervals, the TEV participates in the retail real-time market that runs every 5 minutes. A detailed description is provided below.

EV Day-Ahead Market Participation

The proposed retail day-ahead market participation involves two successive processes, namely quantity optimal scheduling and bid curve formulation. The quantity operational schedule is done based on the formulation presented in (4-76). After the optimized bidding quantities are obtained from day-ahead optimization, a four-point bid curve is constructed as described in Section 4.2.2.1.

To generate the four-point battery agent bid curve requires knowledge of the EV battery planned operating quantity for a given hour (Q_{plan}), day-ahead forecast price ($f_{DA}(t)$), price-sensitivity slope (PM^S), and price intercept margin (PM^I). The process of computing all four points are the same as discussed in Section 4.2.2.4. The only difference is that in V1G mode, EVs are not allowed to export energy and thus the bid curve will be terminated at $Q = 0$ as shown in Figure 47 (a). Whereas, in V2G mode, EVs are allowed to bid energy export. A typical bid curve will look like Figure 47(b).

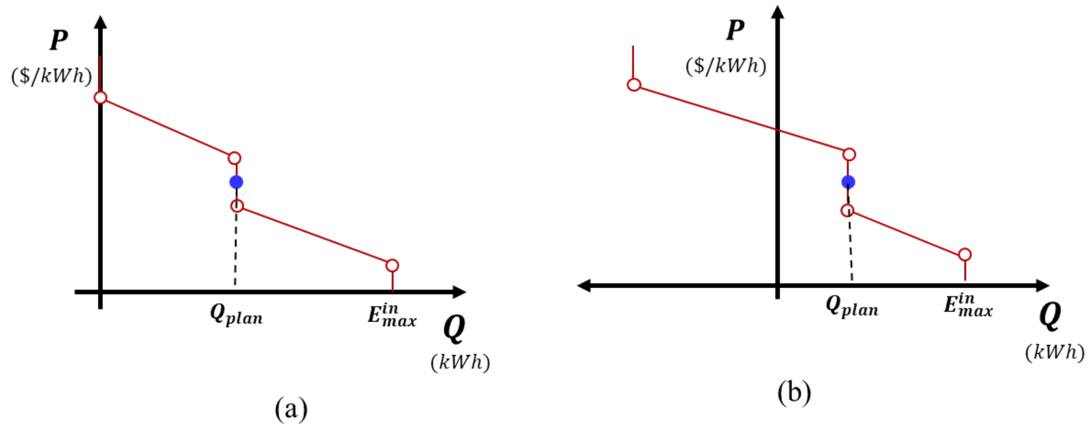


Figure 47. Conceptual illustration of day-ahead four-point bidding for EV agent in (a) V1G and (b) V2G modes.

EV Real-Time Market Participation

Due to the intrinsic uncertainties existing in the system, real-time operation deviates from day ahead. Therefore, the retail real-time market performs the adjustments for the deviations. Unlike the day-ahead bidding, real-time bidding is submitted every 5 minutes. The real-time operation updates its knowledge of the EV SOC from the vehicle charger every 5 minutes, thus updating the remaining operational flexibility in EV for real-time adjustment.

The day-ahead planned quantity and price obtained from scheduling is directly used for the real-time bid curve formulation. However, the Q_plan for real-time bid is updated every 5 minutes by interpolating between the cleared day-ahead quantity of the existing hour and Q_plan for the next hour day-ahead market. This concept of interpolation is explained in Figure 25. Thus, a real-time bid curve with the same slope but interpolated quantity is used every 5 minutes for an hour. As the value for day-ahead optimization gets refreshed, the same procedure repeats.

EV Market Control Mapping

The control implementation module takes the clearing price from the retail real-time market and controls the EV equipment such that operation meets the committed quantity from the bid curve submitted to the market. An actuation signal is sent to the EV charger and inverter to guide its operation. The EV model in GridLAB-D is controlled by the vehicle arrival and departure time in the base case; however, a charger kW signal can override the base case behavior.

EV Performance Evaluation

A small test case with one DSO and 350 residential houses was created for evaluation with 30% EV penetration. The case contains around 100 houses with EVs. Five days in August were simulated and the performance results under V1G and V2G cases were evaluated.

Figure 48 shows the impact of TEV on the aggregated load profile at the substation level. The net load profile with base case EV (blue line) is compared with TEV (orange) and V2G (green) mode. The valley filling effect can be observed in both V1G and V2G where the EV load is shifted from daytime to midnight, thus reducing the peak load. Since V2G can export energy as well, it is able to have a higher load flattening impact by acting as energy source in daytime.

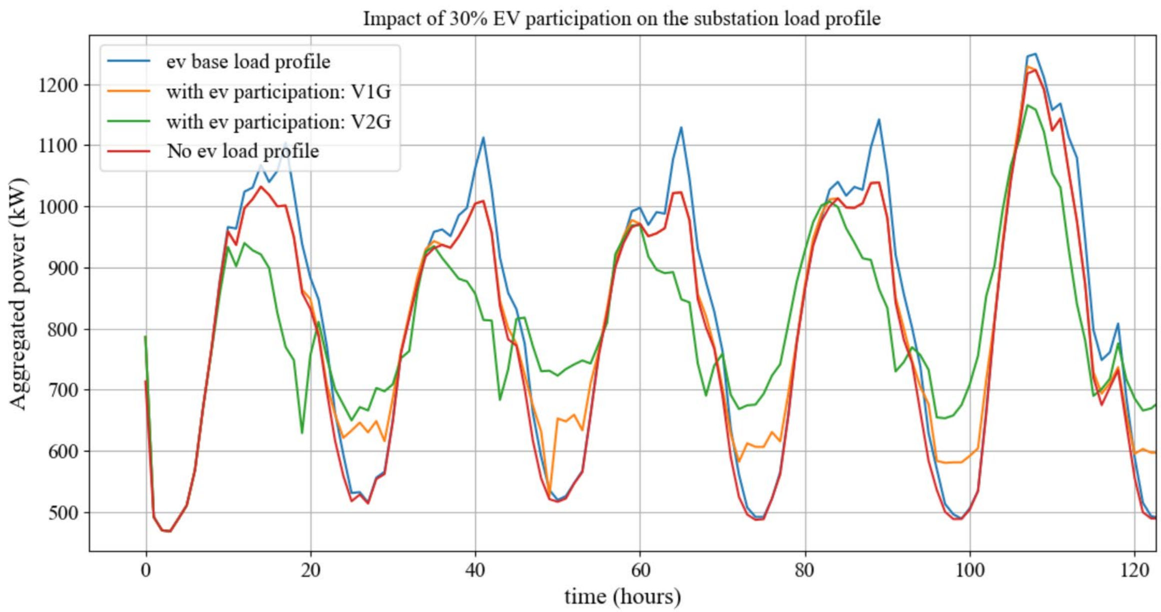


Figure 48. Net load comparison of TEV agent participation in V1G and V2G cases.

Figure 49 shows how retail day-ahead cleared prices for a particular hour evolves through the 48-hour window. Each curve denotes 1 hour as marked in legends. The blue markers denote the price cleared at 10 a.m. of the same day. The evolution of all hours seems to be flat, showing the stable convergence of the day-ahead market clearing process. Figure 50 shows the retail day-ahead and real-time cleared price for the current hour for five days. The real-time cleared prices follow the day-ahead cleared prices closely, reflecting a successful execution of the agent bidding and clearing process.

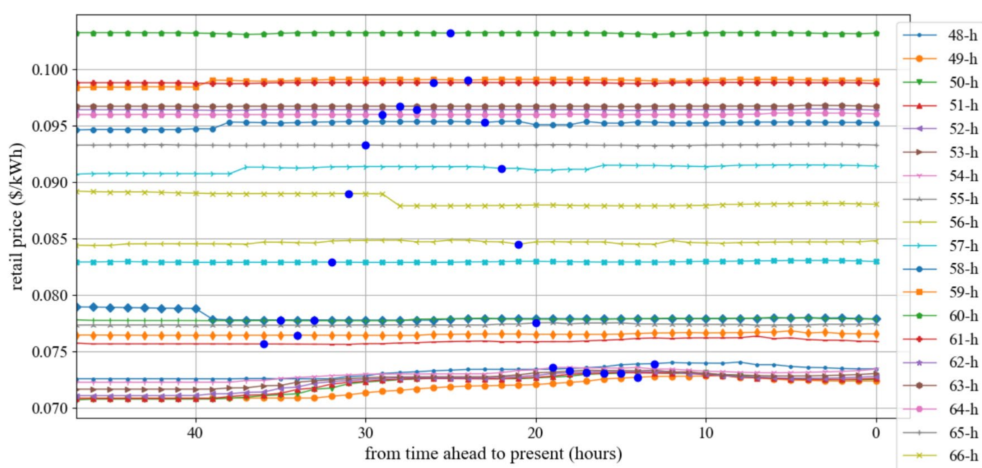


Figure 49. Day-ahead market convergence plot.

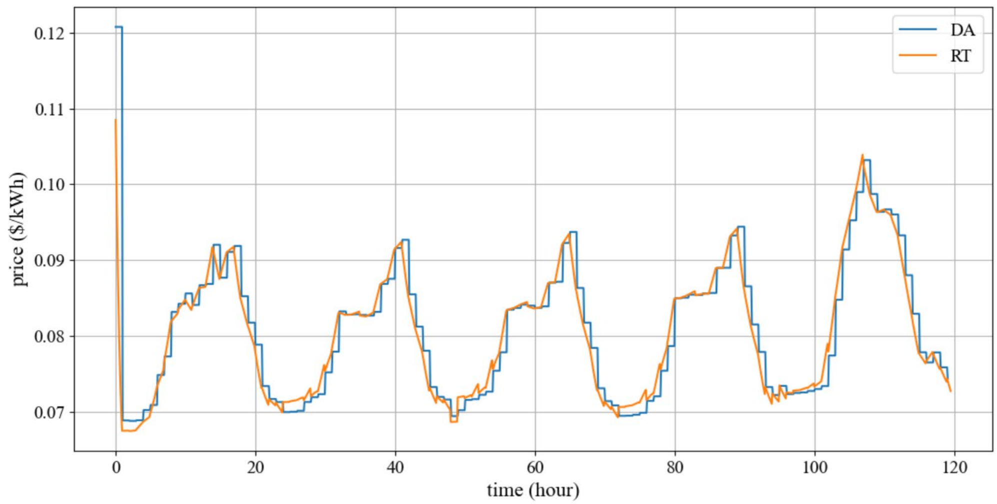


Figure 50. Day-ahead and real-time cleared price profile for five days of simulation.

V1G Case

Figure 51 shows the aggregated EV load (upper) and mean SOC level across all EV agents (lower) in V1G mode. The SOC level gets charged to its maximum every day close to 100% before leaving home. However, it could only discharge to around 85-90%. This happens because most EVs have much higher capacity battery compared to their daily average travel miles. This shows a reasonable scope for V2G where unused SOC can be utilized by exporting energy to the grid.

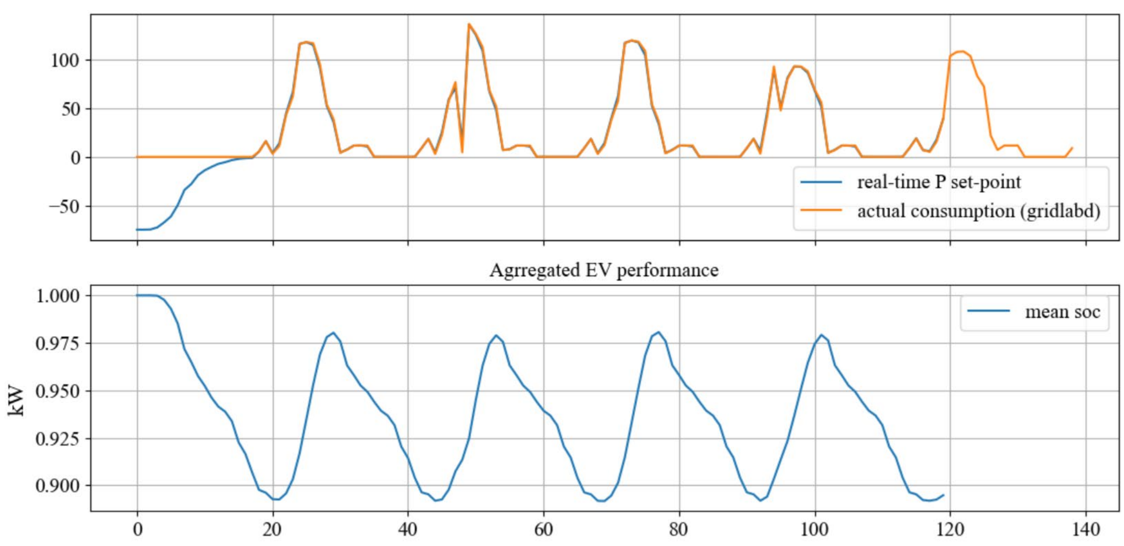


Figure 51. EV performance with transactive participation in V1G case.

V2G Case

A similar plot for V2G is shown in Figure 52 where aggregated EV load can be seen in both directions, i.e., positive means consumption and negative means export of energy. Similarly, the mean SOC level now can get to as low as 60% showing more utilization of battery SOC range.

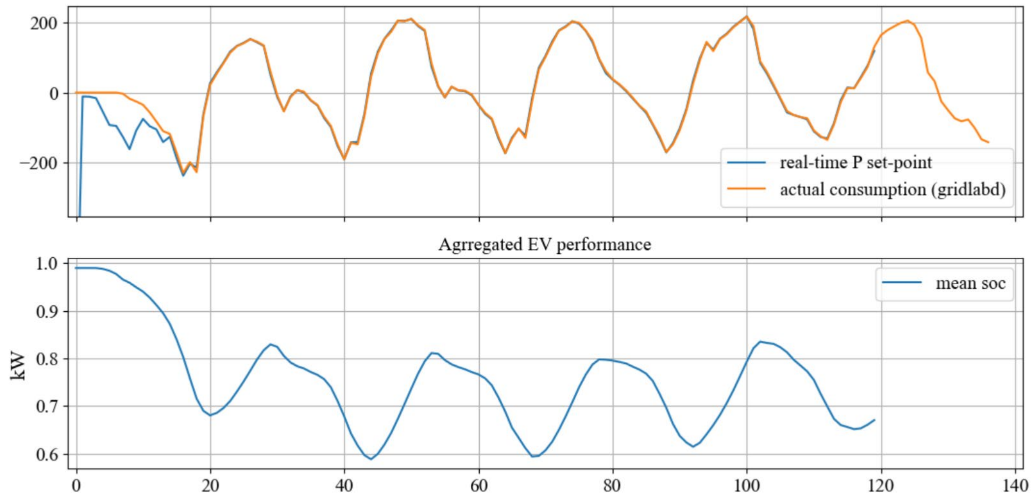


Figure 52. Aggregated EV performance with transactive participation in V2G case: a) sum of EV consumption and b) mean of SOC across all EVs.

4.3 General Market Services

The following services are used for the entire simulation.

4.3.1 Weather Forecaster

The participating customers and LSEs use weather data to forecast the unresponsive loads for future market intervals. Since true knowledge of future weather is unknown, the “true” values are simulated by introducing errors that emulate natural errors of weather forecast systems.

We used two constructs to create the forecasting error. First, the error is random. Second, the level of error for future forecast intervals increases as the intervals go further out in time from the point at which the forecast is being performed. The randomness is created by a random sample of error within the boundary as shown in Figure 53, which demonstrates the error for the three different samplings that can be made: uniform, triangular, and truncated normal. Similarly, Figure 54 demonstrates the comparison of the forecast performance with and without forecast errors. The forecast errors with all three types of sampling are very similar. In DSO+T, random errors are introduced by truncating the normal distribution at 95%.

The weather information for every DSO is collected from a physical solar model (PSM) v3, a meteorological dataset from NASA’s Modern Era-Retrospective Analysis datasets (NREL n.d.). NASA’s original dataset has hourly resolution. These data are then resampled and interpolated to a finer resolution by PSM v3. The downloaded PSM v3 dataset possesses many climate variables such as wind speed, surface pressure, humidity, temperature, and many solar variables. Every DSO uses separate PSM v3 datasets based on their actual location. Every asset and customer within a given DSO utilizes the given set of weather data for that region.

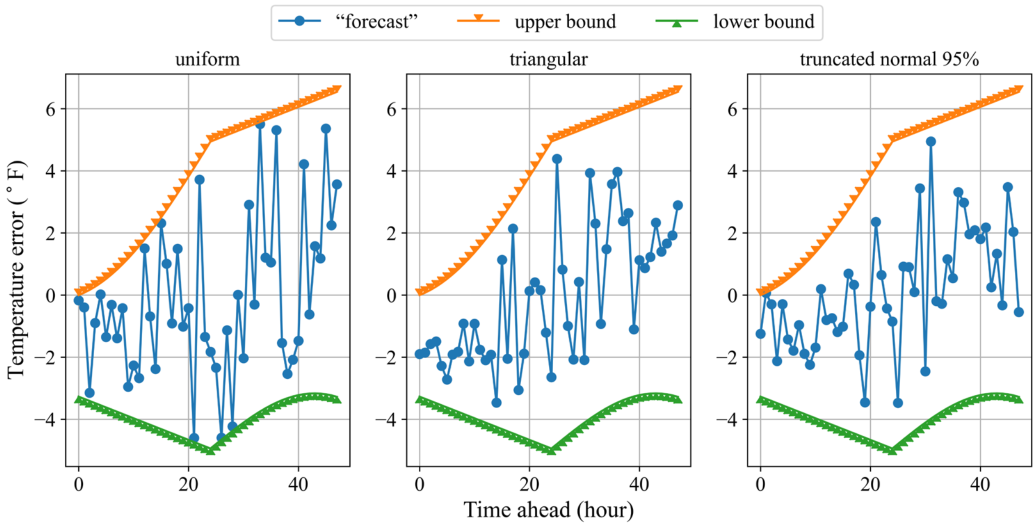


Figure 53. Bounded random error for weather forecasting.

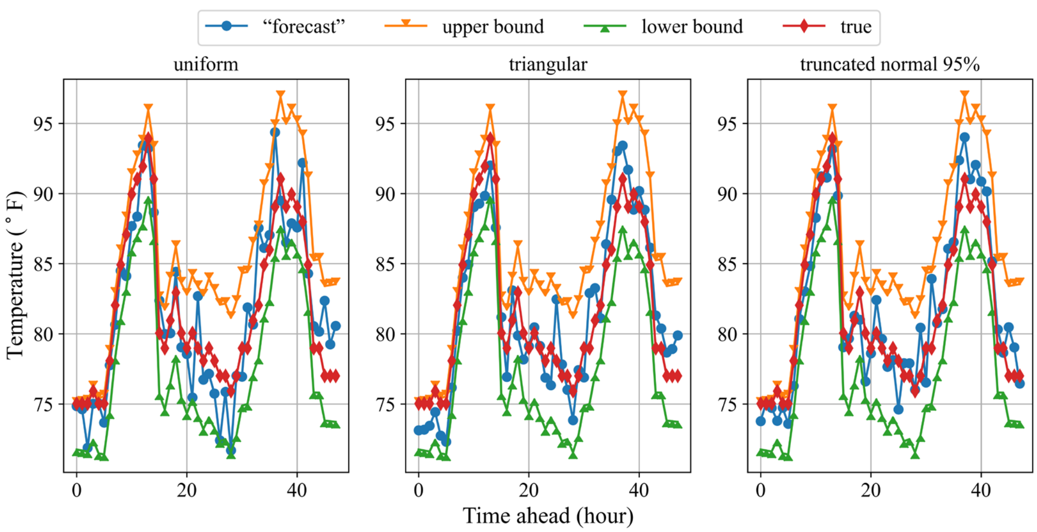


Figure 54. Comparison of weather information with and without error.

4.3.2 LMP Forecaster

The LMP forecaster estimates the wholesale LMP at the DSO's transmission node. The LMP forecast is applied in two situations. First, the forecaster is used as input for the DSO to construct its price-quantity supply curve for the wholesale day-ahead market. Second, the forecaster is used as input for the retail market operator to construct the supply curve for the retail day-ahead market.

To develop this forecast, the DSO+T study uses LMP results from the BAU case simulation. The BAU case has the same transmission system and DSO connection structure as the transactive cases; however, it does not have any DER flexibility participation, i.e., all customers are nonparticipating customers. This assumption should be reconsidered for future studies using LMP forecasts due to the market impact from high penetrations of DERs. Since every node of the transmission system can experience different prices over the course of the simulated year, an

LMP forecast must be developed for each node in the transmission network where a DSO is connected.

The LMP forecaster for each DSO statistically estimates the relationship between the LMP and DSO demand. Statistical evaluation of the ERCOT LMP and load data used for the BAU case found different characteristics for weekends and weekdays; therefore, the forecaster creates a separate model for weekdays and weekends. The Figure 56 illustrates that the quadratic curve fits the majority of actual 2016 ERCOT data well except some discrepancies observed especially toward the maximum quantity for the given transmission node.

Figure 55 illustrates the LMP forecaster weekdays and weekends statistical models constructed from the ERCOT 2016 data for the Houston transmission node. Figure 56 presents the simulated wholesale market LMP forecast of a given transmission node of the simulated ERCOT system.

Once constructed, the LMP forecaster models remain static for application in the transactive simulation cases in the DSO+T study. An arguable improvement to this approach would be to adaptively calibrate the forecaster models as the actual LMP data become available.

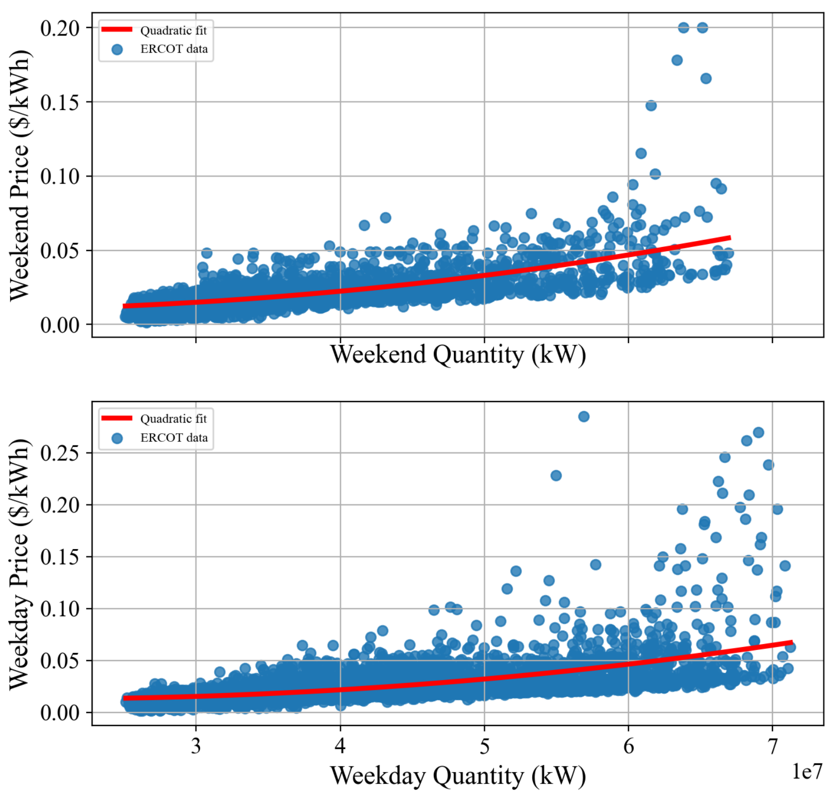


Figure 55. Actual 2016 LMP data from ERCOT Houston.

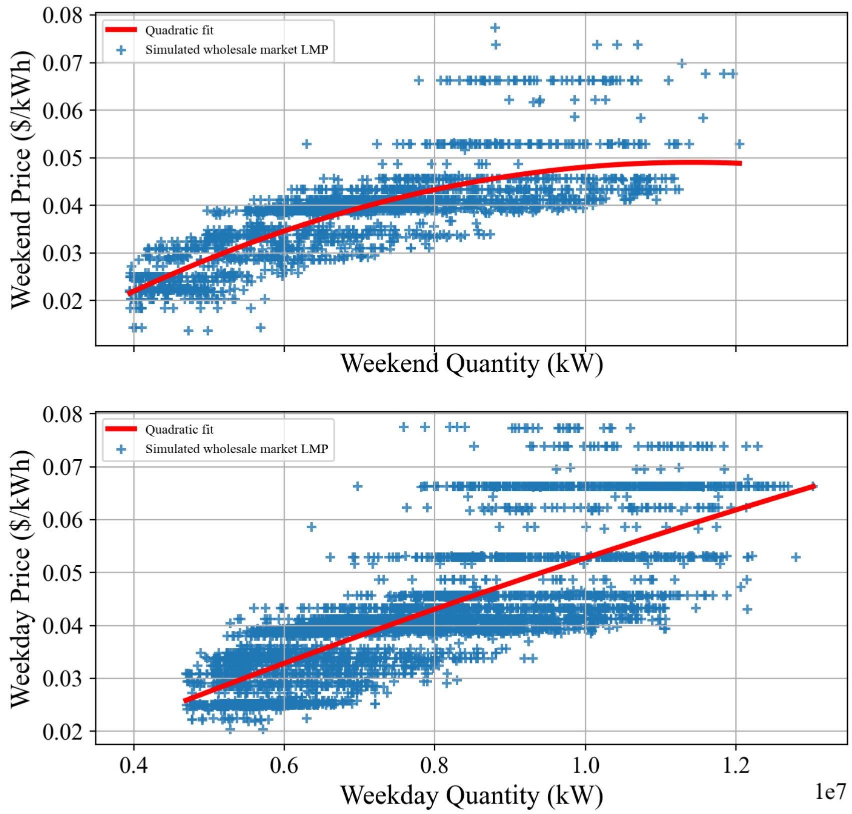


Figure 56. LMP forecaster model for weekends and weekdays using data from BAU simulation.

4.3.3 Load Forecasting

Each participating customer forecasts the loads of its nonresponsive assets. The LSE performs forecasting of all nonparticipating customers assets. The load forecasting methodology is the same for both the participating customer's nonresponsive assets at a site and the LSE's estimate of nonparticipating customers' load. Note, industrial load is modeled as a constant, time-invariant load that is fed into the simulation in a preset data stream.

Depending on the type of nonresponsive assets the customers have, forecasting may need to be done for four different load types (e.g., HVAC, water heater, EV, and other nonflexible load assets). The other nonflexible loads represent plug loads (e.g., refrigerators, dishwashers, electric ranges, and entertainment equipment) and loads for lighting. In the DSO+T study, these nonresponsive loads are modeled as statistically derived quantities, represented parametrically by constant impedance, constant current, and constant power loads, called ZIP loads.

The forecast of each load type is done every hour for the next 48 hours before submitting bids to the periodic transactive retail market. The forecasting is updated every hour to capture the latest information about the resource states. In the DSO+T study, the LSE is responsible for the asset population of all the nonparticipating customers in its jurisdiction and sums the customer site forecasts into one forecast load quantity for use in the retail day-ahead and real-time markets. Each participating customer separately accounts for its nonresponsive assets and adds that load estimate to the bid curves provided by the responsive assets at its site. For the retail real-time market, both LSE and participating customers use one-twelfth (60 minutes divided 5 minutes) of the hourly load forecast. The nonresponsive load forecast methodology for each component is described in detail below.

HVAC: A simplified linear model of room temperature variation due to HVAC operation is used for HVAC load forecasting, as shown below.

$$T_{room}(t) = \varepsilon\, T_{room}(t-1) + (1-\varepsilon)(T_{Out}(t) - \frac{Q(t)}{U_A}) \quad \text{(4-87)}$$

where:

t is the timestep interval in simulation time

T_{room} is the room temperature in °F

T_{Out} is the outside air temperature in °F

Q is the total heat gains added to the air and building mass in Btu

ε is the system inertia, which equals $e^{-t\,U_A/C}$ (unitless)

Q is the heat gains added to the indoor air in Btu

U_A is the building envelope of conductivity to the indoor air in Btu/°F

C is the total thermal mass in Btu/°F

The total heat gains of the house, $Q,$ are the sum of heat gains from the HVAC system (Q_{hvac}), solar heat gains (Q_s), and internal heat gains (Q_i) from house appliances as,

$$Q(t) = -COP * Q_{hvac}(t) * \frac{3412.14}{l} + Q_i(t) + Q_s(t) \quad \text{(4-88)}$$

where, l is a latent factor that is a function of humidity (unitless value) (Chassin et al. 2008). The COP is a coefficient of performance of the HVAC equipment that expresses the efficiency of the given equipment (unitless value). Q_{hvac} is the result of multiplying HVAC power by operating time duration. Q_s is the result of solar irradiance and solar diffuse inflicted on all sides of the building, multiplied by a solar gain factor that reflects the building's properties that influence the solar heat gain. Finally, Q_i (the internal gains) is the heat gain diffused from other house appliances inside the house. Both Q_s and Q_i are obtained from a predefined schedule from the instantiation of the buildings used in the simulation. The detailed modeling is described in Section 4.2.2.2.

The objective of the forecast is to obtain $Q_{hvac}(t)$, i.e., the energy consumption of HVAC in kWh, during hour t. Since we already know the desired room temperature, $T_{desired}[t]$ at hour t, we assume that the room temperature has achieved equilibrium and is equal to the desired temperature, i.e., $T_{room}(t) = T_{desired}(t)$ in (4-88). The resulting $Q_{hvac}(t)$ is constrained by the HVAC kW rating,Q^R_{hvac}, such that $Q_{hvac} \le Q^R_{hvac}$.

Water Heater: The water heater load forecast assumes the actual steady-state water temperature at time t is equal to the desired water temperature set by the user. In the water heater model, the water temperature is expressed in terms of SOHE as detailed in Section 4.2.2.3. $SOHE_{desired}$ is the SOHE that corresponds to the desired water temperature, T_{set}, which is derived from the water heater instantiation process. Consequently, the water heater consumption (Q_{draw}) is computed by setting $SOHE(t) = SOHE_{desired}(t)$ in the following equation:

$$SOHE(t+1) = SOHE(t) + co0 + co1 \times (E_{upper}(t) + E_{Lower}(t) - Q_{draw}(t)) + co2 \times SOHE(t) \quad (4\text{-}89)$$

Where, $E_{upper}(t), E_{bottom}(t)$ denote the consumption of upper and lower heating elements of the water heater in kWh during hour t, the values of parameters $co0$, $co1$, and $co2$ are given in equations (4-13) through (4-15).

Electric Vehicle: EV loads are forecast for their base case behavior in which all the EVs start charging as soon as they arrive home and continue until fully charged. The EV driving schedules (arrival and departure time, total travel miles per day) and EV model parameters (energy capacity, power charging rating, miles/kWh mileage) are known from the model instantiation process (see Vol. 2, Section 10 for more details). Using this information, an EV charging algorithm is used to forecast the EV average consumption at hour t as shown Figure 57.

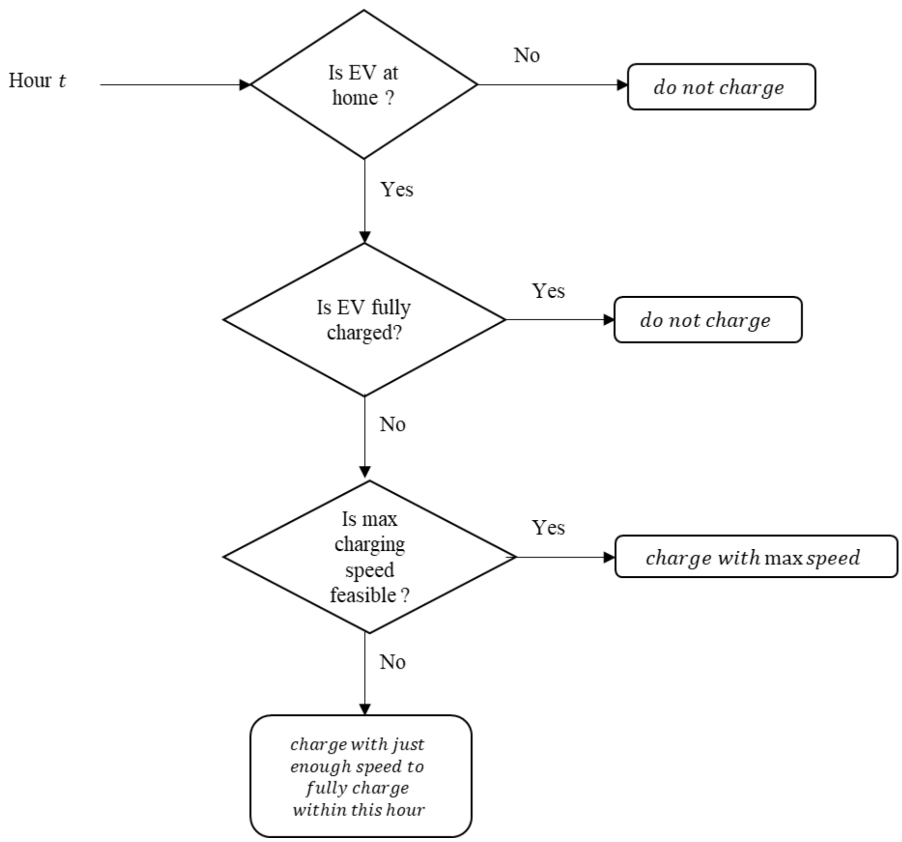


Figure 57. Algorithm to forecast the EV load for hour t assuming base case charging behavior.

Other Nonflexible Loads: Nonflexible loads are defined as the aggregated house appliance loads (except HVAC, water heater, battery, and EV) that are modeled as ZIP loads. The ZIP loads are instantiated in the simulation model with a predefined load schedule. While a participating customer would know this information, it is private (unknown) information to the customer's LSE. An LSE would use historic consumption data to create the ZIP load forecast models and extract load schedules of the aggregate nonparticipating population.

A forecasting error can be added to these values to represent a more realistic scenario for the LSE. The forecast error on top of these models was set to zero for the DSO+T study. Note that the ZIP loads also cause internal heat gains, Q_i, in a building, and therefore factor into the HVAC load forecast (see above).

Example Results: An example of the results of the load forecast methodology is shown in Figure 58. A three-day period is depicted for the total nonresponsive load of an LSE for the moderate renewable BAU case. The mean average percentage error is about 10% for this case. The error is due to using the first-order model for HVAC and water heater forecast.

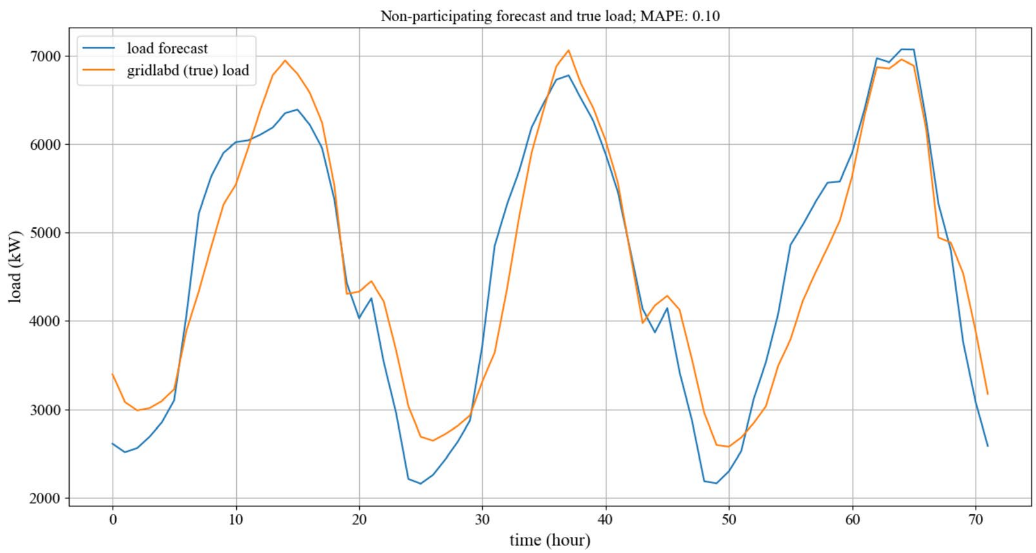


Figure 58. Comparison of the forecast load with the ground truth (GridLAB-D) load.

5 Lessons Learned and Future Research Directions

This section describes the lesson learned while designing and operating the retail markets and transactive agents. The lessons are cataloged to serve as a best practice guide for future research activities as well as to identify promising future research directions.

5.1 Transactive Framework and Agent Design

5.1.1 Retail Market Operation

When aggregating the customers' price-quantity curves and incorporating the forecast of the nonparticipating load for bidding into the wholesale day-ahead and real-time markets, the DSO must ensure that the accuracy and fidelity of the bid curves is preserved. Due to the large number of customers, the chosen aggregation algorithm samples the curves at several points over a fixed-price range. If too small a sample is used, the aggregated curve may not have sufficient resolution to properly represent the price-quantity sensitivity for the DSO wholesale market bid. Poor granularity in the resulting aggregated curve can result in a market-clearing signal sent to the wholesale market and back to the devices that results in significant differences between the energy quantity expected from the price signal versus the quantity from a full-fidelity aggregation. Section 4.2.1.1 provides more details on how this was addressed in this study.

5.1.2 Customer Asset Agent Design

5.1.2.1 Features to Promote Market Convergence

Two key features were implemented in the asset agent and its price-quantity curve to promote the stable operation of the assets and retail market. First, a hysteresis deadband was incorporated in the agent bid curve to make the bids less sensitive to small changes in the prices. This tempers changes to the transactive agents' desired operating position when subject to small price change situations. Second, a quadratic sensitivity term was introduced in the transactive agent decision-making process to make the agent bid less sensitive to small price changes and more sensitive to large price changes. The introduction of such a factor helped the retail markets run more smoothly. Section 4.2.2.1 provides more details on how these two features are included in the agent decision-making process.

5.1.2.2 Features to Avoid Unintended Synchronization of Assets

Designing asset agents to operate devices at more than one timescale requires careful thought, experimentation, and verification. This includes the complexities of designing day-ahead bids so they behave rationally with respect to real-time bids and the asset's actual operation. For example, the application of a smoothing algorithm, such as interpolation, to future (day-ahead) market-cleared quantities is required to ensure they are piecewise continuous in time (see Section 4.2.2.1). This is needed as the hourly day-ahead market solution serves as the basis for the actual assets real-time (5-minute) response. An initial agent design had step changes in the assets' desired hourly day-ahead quantities resulting in large changes in real-time response at the start of each hour. This behavior was common in all assets, synchronizing them at the start of every hour, and resulted in large (multi-gigawatt) spikes in system-wide load, particularly in on/off thermostatically controlled assets like HVAC units.

This is an example of a general challenge in the design of DER coordination schemes: avoiding unintended synchronization of DERs that can result in large disruptive load changes. The DSO+T study also observed this phenomenon in simulation when boundary conditions were (in aggregate) not piecewise continuous in time. For example, an early implementation had BAU thermostat settings that were discontinuous between weekend and weekday operation, resulting in large load spikes. This issue may also arise with the implementation of time-of-use rates for large populations of DERs if, say, all EVs start charging the instant nighttime rates go into effect. It is possible that in actual implementations DER (and asset agent) diversity will help minimize synchronized behaviors of transactive agents and hence help to stabilize market performances. However, a common dynamic retail market signal will still be a potential source for unintended synchronization if not designed correctly.

5.1.2.3 Incorporating Control Mode Transitions within Asset Models

The agents' asset models need to account for changes in asset control modes including any that may occur within the 48-hour load forecast window. For example, an HVAC unit may transition from heating to cooling mode within a 48-hour period during shoulder seasons (e.g., spring or fall). If the asset model is assumed to only operate in one mode for an entire 48-hour window, it will not capture these transitions. This can cause poor-quality quantity forecasts that can change as the forecast window advances, resulting in oscillations in cleared quantities.

5.2 Simulation and Evaluation Lessons Learned

5.2.1.1 Simulation Performance, Initialization, and Convergence

Making the transactive asset agents computationally efficient while maintaining the desired decision-making behavior is important. For field deployment, the algorithms need to be implementable on embedded equipment controllers, customer energy management hubs, or hosted in the cloud. Efficiency and decision accuracy are also important for large-scale simulations to minimize the computational resources required to manage tens of thousands of DERs. Simplified models need to be sufficient to estimate the resource operational dynamics and the transactive agent decision-making process needs adequate optimization algorithms. In the DSO+T study, the design process started with detailed agent models that incorporated nonlinear characteristics to prepare agent operational schedules. But the approach evolved to use simplified, first-order asset models. This simplified the agent decision-making process and improved the computational efficiency (Tbaileh et al. 2021).

Since the annual analysis was performed by simulating 12 separate months, an initialization period was needed at the start of each month to stabilize agent behavior. A settling period of three days was used to mitigate decision performance issues from the initialization status of the assets or prices. Overall market behavior was stable and well behaved with infrequent performance disruptions observed within the first three days.

5.2.1.2 Troubleshooting Issues within Interdisciplinary Co-simulation Environments

Troubleshooting performance issues within the DSO+T study's co-simulation environment was challenging. The complex and interdisciplinary nature of the systems and phenomena being studied (including everything from the control and operation of HVAC systems to the economic dispatch of thermal generators) combined with the standard issues of tool and code debugging exceeded expectations. This was compounded by the computational effort and time required to conduct simulations.

The study plan sought to address this challenge by developing and testing the agents within a separate, leaner test environment (with ~300 customers). In addition, the eight-bus test bench model was used to enable less computationally intense runs of the entire system. However, even with this approach there is a limit to the edge cases and parameter space that can be discovered and evaluated within these partial development environments. Many of the lessons described above were not learned until running annual cases in the integrated eight-bus model. In addition, while there were preliminary design requirements for the agents, additional requirements were discovered when the behavior of the integrated system was evaluated.

Continuing to define and strengthen agent interface definitions, requirements and associated performance tests will ease future development. This study used standardized bid definitions, weather and price forecast services, and customer preference (slider) setting formulations. Such standardization reduced the development and testing effort. In addition, test cases and expected performance identities helped determine issues prior to the fully integrated co-simulation. Examples included testing asset agent behavior on price signal edge cases, ensuring the response to constant prices matched that of nonparticipating assets. In addition, testing with the customer slider set at zero (maximum comfort versus response) confirmed that the asset agent response matched that seen for nonparticipating assets.

This experience suggests the need for greater implementation of continuous integration and continuous delivery software development tools and best practices. How best to do this for projects that involve co-simulation across myriad tools (many of which are only partially tested) and organizations is an open question. In addition, the breath and complexity of the systems and technologies being studied makes understanding the coverage of testing very difficult. The continued implementation of automated testing combined with greater adoption of agile development practices will help in these areas.

5.2.1.3 Ensuring Comparable Load Forecast Accuracy between Cases

Supporting services such as weather, price, and load forecasts need to be carefully controlled to have similar behavior in each of the cases being studied. For example, any load forecast performance bias between the BAU and transactive cases can greatly alter system prices and the resulting economic evaluation. If a systematic bias in load forecast occurs, it can have large and nonlinear implications on generation scheduling and dispatch, thus influencing the resulting wholesale market prices. Even infrequent (~1-2%) inaccuracies in bids can be amplified by the ability of market prices to reach $2,000/WM-hr (a ~100x increase over typical values). For this reason, comparisons of bid performance and accuracy were made for all cases to ensure consistency.

5.3 Future Research and Evaluation Needs

In the wholesale marketplace, the generator owner-operators bid their price-quantity curves into the day-ahead and real-time marketplace. In the study, the DSOs were wholesale market price takers. The complexity of setting up the wholesale market simulation to run stably over the varying daily, weekly, and monthly conditions even in the BAU case led to lack of confidence in the robustness of the wholesale market simulation, and therefore, this simplification. Future work should study the impact of DSO price-quantity curve bidding into the wholesale market along with a minimum (fixed) quantity for the nonresponsive demand.

Future work should also look at innovative agent bidding strategies that manage risk across the markets. In the retail case, the customer agents' strategy in the study was to bid to best meet their forecast need. All additional flexibility would be reserved for real-time market correction. Other strategies could look at market behavior statistics and hedge customer positions long or short in the day-ahead market based on flexibility projections for volatility in the real-time market. Such strategic approaches to financial and comfort risk management remain a significant area of research.

This study demonstrated that relatively simple asset models and control approaches are sufficient to estimate the resource operational dynamics in the transactive agent decision-making process. In particular, the agent asset models only included first-order effects and the LMP forecaster was based on forecast net load at each system node. A future full-scale implementation of a transactive energy coordination scheme will incorporate more sophisticated and accurate load and price forecasts than were used in this study. The degree to which improved asset and forecast models can improve accuracy and system operation, and the resulting value of coordinating DER operation, is an open research question. Conversely, there is a benefit in understanding the lower bound on adequate asset modeling and forecast accuracy required for reasonable system coordination. This will be particularly true for understanding system performance during rare long-tail events such as large-scale system outages and extreme weather and price conditions.

Additional assets can be modeled and their impacts analyzed. For example, automated lighting systems at residential, commercial, industrial, and community levels deserve investigation. Refrigeration systems at various scales may also have significant impacts. Due to the high specialization required to model industrial facilities, the impacts of moderating the load (or generation) from these sources of flexibility represent an extremely large segment that can contribute to efficiently balancing supply and demand in future scenarios.

Finally, the objective of this study was to design and integrate a transactive energy coordination scheme into existing wholesale markets, in this case an hourly day-ahead and 5-minute retail market. As such, the retail market operator receives wholesale market information for a given time only twice, at 10 a.m. the day before and in real-time. It is expected that more frequent information on wholesale market prices, for example from an intraday hourly market clearing, would improve DER response and value contribution. The degree of improvement and how best to integrate into an intraday wholesale market are open questions.

6 Conclusions

The DSO+T study investigates the impacts of coordinating the operation of large quantities of DERs in select future scenarios involving moderate to high renewable penetration and flexible assets including EVs, batteries, and controllable loads. The chosen scenarios and modeling of coordinated operation of DER assets on a large regional basis that includes integration with the bulk transmission system and wholesale markets has been a significant undertaking in design, development, and debugging.

The design of the transactive energy retail markets and their integration through a DSO to the wholesale markets allows for a holistic investigation of how coordinated operation of DER can contribute to effectively transitioning to a high renewable future that includes greater electrification of transportation and other energy-consuming processes.

Such a large simulation undertaking requires thoughtful compromises in engineering and economic market design tradeoffs to produce results that are representative and directionally supportable. While the transactive energy design used for this study is only one of many design approaches that could be chosen, the behavior of the markets and the asset agents' decision-making processes have proven to be stable.

But this is only a beginning. More needs to be done to explore and improve agent and marketplace behavior. Contributions from other asset and customer classes can contribute to greater DER flexibility than simulated in this study. More accurate predictions of weather and market prices will also influence decision-making at local and regional levels. Diversity of decision-making processes may also have operational smoothing and resiliency effects.

The design of the asset models, markets, and agent behavior in the DSO+T study simulations indicates that distributed decision-making approaches are a viable method for coordinating DER flexibility. By providing access to well-designed markets, participant value exchange becomes an explicit part of a balanced solution that is adaptable to different regions, policies, and technology advances.

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