PNNL-27235 Part 1

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Transactive System

Part I: Theoretical Underpinnings of Payoff Functions, Control Decisions, Information Privacy, and Solution Concepts

December 2017

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U.S. DEPARTMENT OF ENERGY
Prepared for the U.S. Department of Energy
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Summary

The increased penetration of renewable energy has significantly changed the conditions and the operational timing of the electricity grid. More flexible, faster ramping resources are needed to compensate for the uncertainty and variability introduced by renewable energy. Distributed energy resources (DERs) such as distributed generators, energy storage, and controllable loads could help manage the power grid in terms of both economic efficiency and operational reliability. In order to realize the benefits of DERs, coordination and control approaches must be designed to enable seamless integration of DERs into the power grid. Transactive coordination and control is a new approach for DER integration, where individual resources are automated and engaged through market interaction. Transactive approaches use economic signals—prices or incentives—to engage DERs. These economic signals must reflect the true value of the DER contributions, so that they seamlessly and equitably compete for the opportunities that today are only available to grid-owned assets. Value signals must be communicated to the DERs in near-real time, the assets must be imbued with new forms of distributed intelligence and control to take advantage of the opportunities presented by these signals, and they must be capable of negotiating and transacting a range of market-driven energy services. The concepts of transactive energy systems are not new, but build upon evolutionary economic changes in financial and electric power markets. These concepts also recognize the different regional structures of wholesale power markets, electricity delivery markets, retail markets, and vertically integrated service provider markets. Although transactive energy systems are not revolutionary, they will be transformational in their ability to provide flexibility and operational efficiency.

A main goal of this research is to establish useful foundation for analysis of transactive energy systems and to facilitate new transactive energy system design with demonstrable guarantees on stability and performance. Specifically, the goals are to (1) establish a theoretical basis for evaluating the performance of different transactive systems, (2) devise tools to address canonical problems that exemplify challenges and scenarios of transactive systems, and (3) provide guidelines for design of future transactive systems. This report, Part 1 of a two part series, advances the above-listed research objectives by reviewing existing transactive systems and identifying a theoretical foundation that integrates payoff functions, control decisions, information privacy, and mathematical solution concepts.

Acknowledgments

The authors are grateful to Christopher Irwin of the U.S. Department of Energy Office of Electricity Delivery and Energy Reliability for supporting this research and development effort.

Acronyms and Abbreviations

AEP	American Electric Power
AHU	air-handling units
DER	distributed energy resource
DLC	direct load control
HVAC	heating, ventilation, and air conditioning
PNNL	Pacific Northwest National Laboratory
PNWSGD	Pacific Northwest Smart Grid Demonstration
PRC	price responsive control
R&D	research and development
RTP	real-time pricing
TeMix	Transactive Energy Market Information Exchange
TFS	transactive feedback signal
TIS	transactive incentive signal

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1.0 Introduction

Electricity demand has been steadily increasing (EIA 2011). One way to keep up with demand is to build more generation facilities. However, planning generation capacity based on peak demand could leave much generation capacity idle when peak demand increases faster than base demand. A more appealing solution is to integrate renewable energy into the power grid, which could significantly reduce fossil fuel consumption and greenhouse gas emissions. Renewable integration is growing because of environmental concerns and economic requirements. However, integration of extensive renewable energy into the power grid imposes challenges to the conventional supply-side control paradigm. As pointed out in (CAISO 2010, Makarov et al. 2009, Smith et al. 2007), it will substantially increase the need for operational reserves to absorb the variability of renewable energy so that supply and demand balance instantaneously and continuously. If additional reserves are still required to from conventional generators, it will diminish the net carbon benefit from renewable integration, reduce generation efficiency, and eventually become economically untenable.

Besides supply-side control, there has long been interest in using electric loads to help balance supply and demand; this is termed demand-side control. Development of communication and computation techniques enables real-time control of electric loads (Brooks et al. 2010). When properly coordinated and controlled, aggregated end-user loads can provide various grid services that were traditionally provided by generators (Callaway and Hiskens 2011) and satisfy the requirements of speed, accuracy, and magnitude. Because end-user loads usually have large population size and high aggregated ramping rate, demand-side control offers enormous potential to mitigate the variability and uncertainty introduced by renewable generation.

A simple form of aggregated load control is direct load control (DLC), where the aggregator (utility companies, load serving entities, or curtailment service provider) can remotely control end-user loads based on prior mutual financial agreements. Traditional DLC is usually concerned only with services such as peak shaving and load shifting (Chen et al. 1995, Chu et al. 1993, Kurucz et al. 1996). Lately, DLC has begun focusing on modeling and control for a large population of end-user loads such as thermostatically controlled loads (Bashash and Fathy 2013, Callaway 2009, Kalsi et al. 2012, Kondoh et al. 2011, Mathieu et al. 2013, Zhang et al. 2013), plug-in electric vehicles (Liu et al. 2013, Vandael et al. 2013), and data center servers (Chen et al. 2013, Li et al. 2014) to provide services including frequency regulation and load following. Some of these DLC approaches require fast communication between the aggregator and individual loads.

Although DLC can achieve reliable and accurate aggregated load response, its practical application is greatly challenged by privacy and security concerns of residential customers. It is usually difficult in practice to obtain private information that is required for the implementation of DLC approaches. As an alternative to DLC, price responsive control (PRC) protects customer privacy by sending price signals to end-user loads so that they can individually and voluntarily manage their local demand. Common examples of PRC include time-of-use pricing, critical-peak pricing, and real-time pricing (RTP) (Allcott 2011, Borenstein et al. 2002, Chao 2010, Hogan 2010). Recently projects (Faruqui et al. 2010) have demonstrated the performance of PRC in terms of payment reduction, load shifting, and power shaving. However, these approaches either directly pass the wholesale energy price to end users or modify the wholesale price in a heuristic way. Therefore, it cannot achieve the predictable, reliable aggregated load response required of demand-response applications.

Transactive control and coordination is a new type of coordinated load control for demand response. Concepts from microeconomic theory (Mas-Colell et al. 1995) are combined with control theory to design strategies to coordinate and control the aggregated response (Fahrioglu and Alvarado 2000, Samadi et al.

2012b). Transactive control has advantages of both PRC and DLC. It preserves customer privacy by using internal price as the control signal. However, the internal price is systematically designed according to specific control objectives, which can be dramatically different from the wholesale price (see, for example, (Chen et al. 2010a, Li et al. 2011a)). Hence, it can also have more predictable and reliable aggregated load response.

The GridWise® Architecture Council defines transactive energy as, "a system of economic and control mechanisms that allows the dynamic balance of supply and demand across the entire electrical infrastructure using value as a key operational parameter" (The GridWise Architecture Council 2015). Several field demonstration projects in the U.S. and Europe have proven the technology feasibility of transactive energy. The Olympic Peninsula Demonstration (2006–2007) (Fuller et al. 2011, Hammerstrom et al. 2007) was the first proof-of-concept demonstration project in the U.S. that used a double-auction market for congestion management. Building upon the Olympic Peninsula Demonstration, the AEP (American Electric Power) gridSMART® Demonstration (2010–2014) (Widergren et al. 2014, Widergren et al. 2014) also used the double-auction market for residential load coordination and incorporated RTP. The Pacific Northwest Smart Grid Demonstration (PNWSGD) (2010–2015) (Hammerstrom et al. 2015, Huang et al. 2010) used peer-to-peer negotiation based on consensus principles to coordinate the operation of DERs. PowerMatching City (2009–2015) (Kok et al. 2012) was a demonstration project in Europe that used a double-auction market to balance supply and demand.

In Part I of this report, we review literature on existing transactive energy systems. Using principles from microeconomic theory, we develop a theoretical foundation for the systematic analysis and design of transactive energy systems. Internally consistent payoff functions, control decisions, information privacy, and mathematical solution concepts are offered. In Part II, we develop performance measures for analyzing different transactive approaches and apply the theory of Part I to analyze transactive energy systems deployed in the AEP gridSMART® demonstration project and the PNWSGD project, respectively.

2.0 Transactive Energy Systems

According to the GridWise® Architecture Council definition of transactive energy, "value" implies the transactive energy price, which enables customers of all sizes to join traditional providers in producing, buying, and selling electricity using automated control to drive a more reliable and cost-effective power grid. In terms of customer privacy, scalability, and efficiency, transactive energy systems have clear advantages over coordination methods such as DLC and PRC. In this section, several major projects in the U.S. and Europe that use transactive approaches to coordinate DERs with system operations will be introduced and reviewed.

2.1 Olympic Peninsula Demonstration

The Olympic Peninsula Demonstration project (Hammerstrom et al. 2007) was one of the first transactive energy demonstration projects. It took place in an area of the Olympic Peninsula of Washington state that receives electricity through a radial transmission connection to the Pacific Northwest power grid. The project tested the potential for coordinating DERs to postpone or eliminate the need for a transmission upgrade. The project used a 5-minute double-auction market to coordinate four large municipal water pumps, two backup diesel generators, and residential demand response from electric water- and space heating systems in 112 homes. The project established the viability of transactive energy to achieve multiple objectives: system peak load and distribution constraint management; wholesale price purchases by the utility; and residential, commercial, and municipal energy cost savings. The market received supply bids from the utility based on a markup of the local wholesale energy price. The diesel generators' bids were based on the actual fixed and variable costs incurred for operation. The pumps' bids into the market were based on water reservoir levels they regulated. Residential demand-response equipment allowed the households to specify their automatic price-response preferences. To capture their preferences, a selection of comfort settings was devised, each selection named to indicate ranges between most comfortable (not price responsive) to most economical (highly price responsive). The 5-minute market determined the clearing price for energy and broadcast that to the market participants. Each participant's bidding equipment would operate based on whether his bid was higher or lower than the market-clearing price. Besides coordinating the price-responsive resources with wholesale price fluctuations, the transactive system also managed congestion on a distribution circuit, by managing all of the devices as if they were on one circuit and seasonally adjusting the capacity setting of that circuit to exercise constrained operating conditions. The project kept the imported capacity of the circuit below the constraint for all but one 5-minute interval over the entire project year. The technical details of the transactive approach adopted in this project will be described in the next subsection.

2.2 AEP gridSMART® Demonstration

Building upon the Olympic Peninsula Demonstration project, the AEP gridSMART® demonstration project (2010–2014) had an RTP component, called SMART Choice®,[1] that used a 5-minute double-auction market to dispatch participating responsive loads on each of four distribution circuits (Widergren et al. 2014, Sep. Widergren). The RTP experiments ran during the late spring and summer of 2013 and involved four feeders with approximately 200 participating households. The preferences of household occupants were reflected in software agents that developed an overall price flexibility curve for the residential heating, ventilation, and air conditioning (HVAC) units to be coordinated with the market system. Then, a market-clearing engine at the operations center aggregated the bids from all households

[1] SMART Choice is a registered trademark of AEP Ohio.

to form a price-sensitive demand curve for the distribution circuit and calculated a clearing price and a supply bid, which incorporated the regional market operator's (PJM) 5-minute wholesale locational marginal price for electricity. The clearing price was finally broadcast back to the households and captured in the billing system according to a tariff approved by the regulator, the Public Utility Commission of Ohio. An overview of the RTP system design is presented in Figure 1.

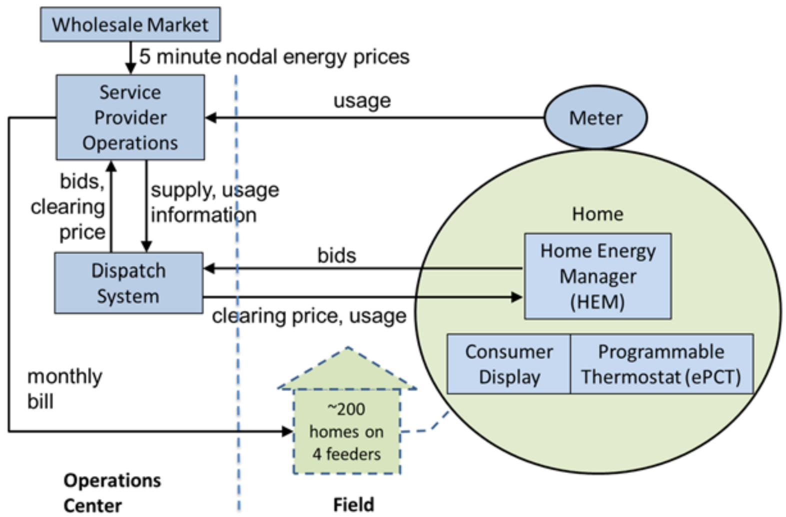

Figure 1. Design Overview of the AEP Ohio gridSMART® RTP System

The transactive approach based on a 5-minute double-auction market is as follows:

- At the beginning of each market cycle, the local controllers of individual household HVAC loads first calculate the bidding price λ_{bid} based on the current room temperature T_c and the local bidding curve as shown in Figure 2. This bidding curve is determined by several parameters. The parameters T_{desired}, T_{min}, and T_{max} are directly specified by users, where T_{desired} is the desired indoor air temperature setpoint, and T_{min} and T_{max} are the lower and upper bounds of the acceptable indoor air temperature setpoint. The parameters λ_{avg} and σ are the average and standard deviation, respectively, of the electricity prices over a past period. The parameter k is a positive number derived entirely from the owner's preference of indoor air temperature setpoint versus electricity price. Then, individual household HVAC loads submit their bids to the market. Each bid consists of a bidding price and a bidding quantity.

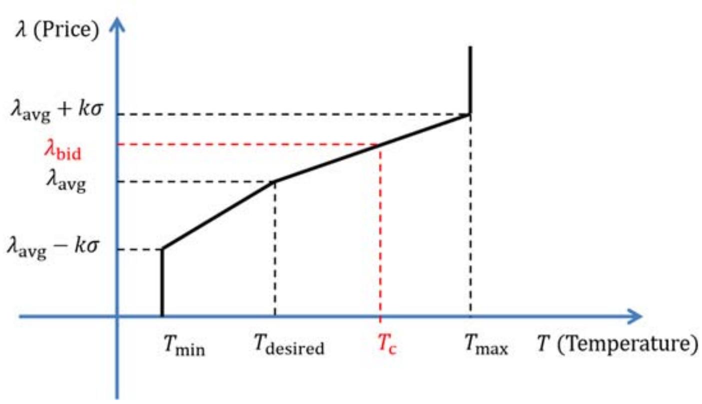

Figure 2. Determination of Bidding Price

- After receiving all the bids from individual HVAC loads, the market sorts the individual bidding prices in decreasing order to form a demand curve, shown in green in Figure 3, where the unresponsive load (P_{uc}) is assumed to bid a price at the price cap (λ_{cap}).
- The market also forms a supply curve by using a base price obtained from the wholesale locational marginal price and the feeder capacity limit.
- When there is no congestion, that is, the feeder capacity limit P_{lim} is not exceeded, the cleared price (λ_{clear}) is the new base price and the cleared quantity (P_{clear}) is determined by the intersection of the demand curve and the horizontal part of the supply curve as shown in Figure 3.

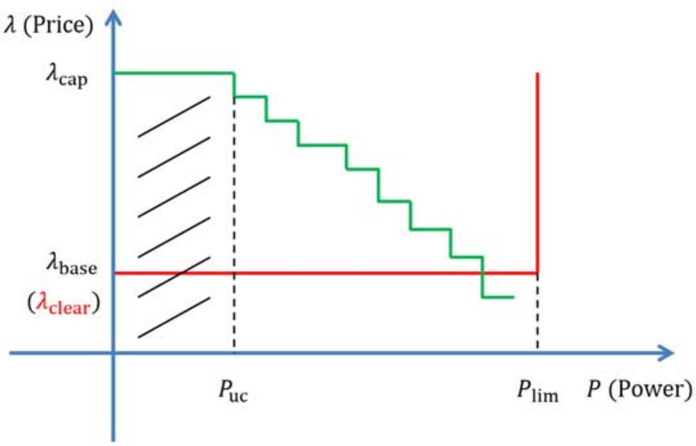

Figure 3. Market Clearing without Congestion

- When there is congestion, that is, the feeder capacity limit is reached, loads are reduced according to the individual bids at the distribution feeder level. The cleared quantity (P_{clear}) is the feeder capacity (P_{lim}). The cleared price (λ_{clear}) is determined by the intersection of the demand curve and the vertical part of the supply curve as shown in Figure 4. In this case, the clearing price λ_{clear} will be greater than the price of supply (λ_{base}). If the congestion persists, more and more responsive loads lose their flexibility, and the market will clear at the price cap (λ_{cap}).

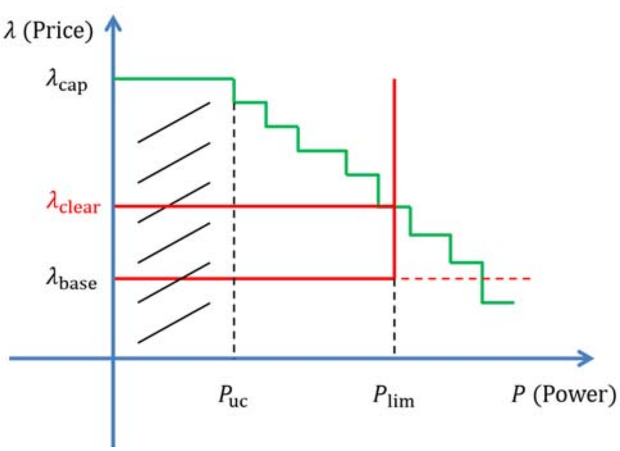

Figure 4. Market Clearing with Congestion

- After the market clears, the clearing price is broadcast back to household loads. The local controllers map the clearing price to local temperature set points according to the bidding curve, as shown in

Figure 5. This new temperature set points will be used as the local control and maintained until a new market cycle begins in 5 minutes.

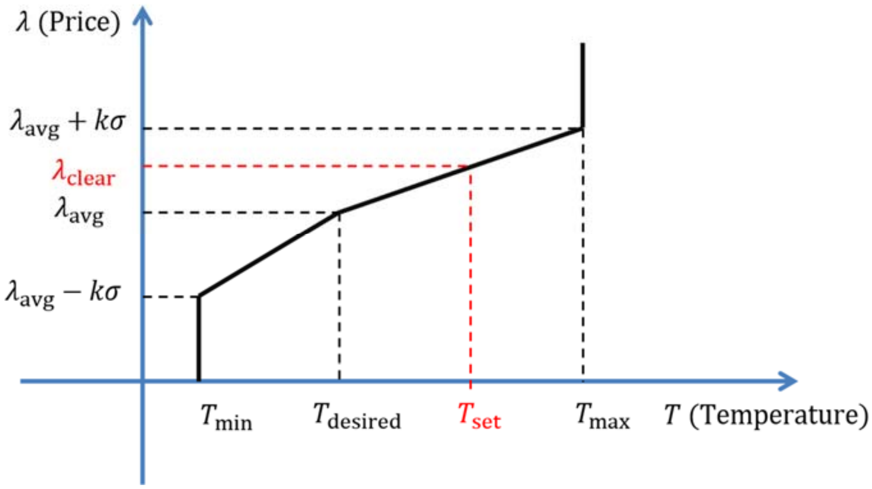

Figure 5. Determination of Local Control Input

- During congestion periods, consumers pay at a clearing price that is higher than the base supply price, which results in a congestion surplus to the utility. This surplus (the red area in Figure 6) is returned to the consumers in the form of rebates to make the service provider revenue neutral. An incentive mechanism is also used to reflect the value of load reduction, which rewards the consumers who are most flexible to price changes. The incentive (the blue area in Figure 6) is computed as a product of the actual consumed energy and the difference between the cleared price and the base supply price.

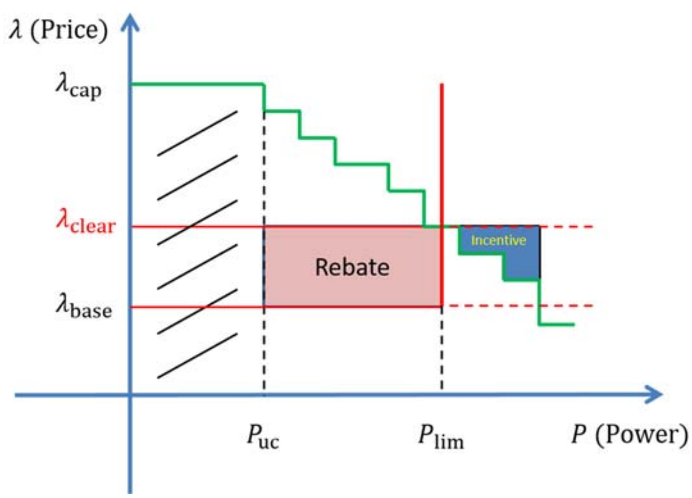

Figure 6. Congestion Surplus Rebate and Incentive

2.3 PowerMatching City Demonstration

PowerMatching City was a demonstration project in Europe that used simultaneous optimization for energy trade and active distribution management. PowerMatching City is located in the Hoogkerk suburb of Groningen in The Netherlands. This living smart grid community was officially opened in April 2010. PowerMatcher, the major coordination mechanism in this project, is designed based on the concept of transactive energy. Various residential appliances, electric vehicles, and wind turbines are interfaced with the PowerMatcher software to operate PowerMatching City as a virtual power plant (Kok et al. 2005, Kok 2013).

In PowerMatcher, an electronic exchange market is used to determine the supply or demand amount for each device agent. The electronic market has a tree structure of supply and demand aggregators called "SD-Matchers." Each SD-Matcher aggregates the demands of the devices and SD-Matchers under it, and the SD-Matcher at the top of the tree (the root SD-Matcher) determines the price. The root SD-Matcher can also define the characteristics of the markets, such as the time slot length, the time horizon, and the execution time (e.g., "every 15 minutes," "every day at 12:00"). At each execution time, the root SD-Matcher requests bids from all directly connected agents, which include the aggregate bids from devices. The root SD-Matcher then determines an equilibrium price and sends it to the devices. Each device can determine its allocated power based on the received market price and its own bid function.

The devices are categorized by their controllability:

- Shiftable operation devices: controllable devices such as washers, dryers, and swimming pool pumps that have a fixed supply or demand over time.
- External resource buffering devices: controllable devices such as electrical heating/cooling devices and heat pump devices that have certain operation flexibility.
- Electricity storage devices: controllable storage devices that react to market prices and try to buy energy at low prices and sell at high prices.
- Freely controllable devices: devices such as diesel generators that are fully controllable within certain limits. These devices' bidding strategies are highly dependent on the marginal costs of the electricity production.
- Uncontrollable devices: solar and wind energy systems. These devices must accept the market prices.
- User-action devices: uncontrollable devices that are operated directly by users. These devices are similar to stochastic operation devices and must accept the market prices.

The transactive approach deployed in this demonstration project is similar to the one used in the Olympic Peninsula and AEP demonstration projects that is based on the double-auction principle. For each controllable device, a demand function states the agent's demand at a price. For generators, the demand function has a negative value at each price. Each device submits the full demand function to the SD-Matcher above it through line agents. The line agents perform the demand function propagation and the price back propagation over the network lines they represent. Depending on a device's current status, its bids can be changed at any time. The intermediate SD-Matchers aggregate all incoming bids of the nodes that are directly connected to them and pass the bids towards the top of the tree. The root SD-Matcher clears the market by determining a market price at which supply and demand match, and then sends the price down through the tree structure.

2.4 Pacific Northwest Smart Grid Demonstration

Based on the successful implementation of transactive control concepts during the Olympic Peninsula Demonstration project (Hammerstrom et al. 2007), the PNWSGD project (2010–2015) featured an innovative transactive system aimed at synchronizing demand and supply for a generation-driven operation of the grid (Hammerstrom 2013, Hammerstrom et al. 2015). The PNWSGD project included multiple states and cooperation from multiple electric utilities, including rural electric co-ops and investor-owned, municipal, and other public utilities, as indicated in Figure 7. There were 55 unique instantiations of distinct smart grid systems demonstrated at the project sites. This project deployed a transactive system to coordinate the operation of DERs and addressed regional objectives, including mitigation of renewable energy intermittency and flattening system load. This was accomplished by engaging users and responsive assets throughout the participating areas of the grid to collaborate with the supply side to improve the system reliability and efficiency by reducing system peaks, reducing expenses, and mitigating challenges associated with integration of variable supply provided by renewable energy resources, such as wind. The transactive control methodology proposed by the PNWSGD project offers procedures and rules that would help transform the power grid into a smart grid.

In the PNWSGD project setting, negotiations are based on value-based principles, but the signals do not necessarily have to account for monetary or revenue exchanges. An iterative process between players is needed to ensure convergence to a solution. The approach is seeking a multi-objective optimum based on the exchange of value between participants. The basic principles behind the PNWSGD consensus-based transactive mechanism are

- bidirectional communication
- incentives and feedback communicated via one nodal signal
- simultaneous engaged multiple operational objectives and responsive assets
- interoperability
- 24/7 response
- end-user friendly
- distributed control facilitator
- dynamic signal on multiple time scales.

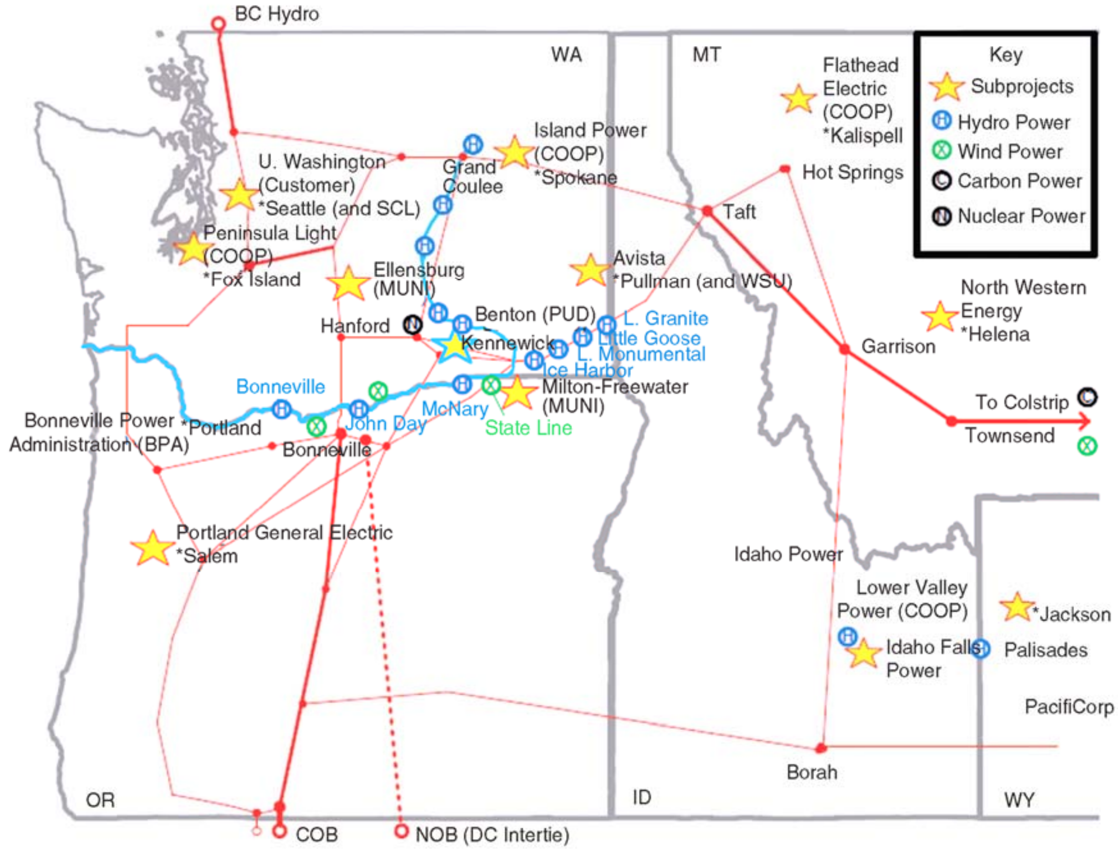

Figure 7. Geographical Region of the PNWSGD Project, Including Participants and Major Generation and Transmission

The four main components of the PNWSGD transactive control are

- transactive nodes – locations or pieces of equipment in the electrical connectivity architecture through which power flows
- transactive signals – the incentive signals coming from the nodes upstream, and the related generated feedback signal to be sent back
- responsive assets – the principal drivers of the transactive control system that directly influence the electrical energy consumption
- enabling assets – any of the information, communication, and metering equipment and technologies that cannot by themselves modify energy consumption, but are integral parts of the system.

The PNWSGD comprised 27 transactive nodes: 14 transmission zone nodes representing large areas of the Northwest transmission system and 13 utility-site nodes corresponding to the distribution circuits owned by 11 distribution utilities in the Northwest. These nodes exchange two types of transactive signals:

- transactive incentive signal (TIS) – the unit cost of the delivered energy requested by the transactive feedback signal
- Transactive feedback signal (TFS) – the energy flowing from one transactive node to the neighboring one during a given time interval.

All transactive signals are represented as a series of triplets, with each triplet comprising a time interval, a value, and a level of confidence to qualify the value. Based on the time horizon of the transactive control strategies considered, the PNWSGD project's system architects decided to support forecasts over 56 time intervals ranging from five minutes to a day, and extending more than three days into the future. Figure 8 provides a high-level summary of the transactive-node approach developed for this project.

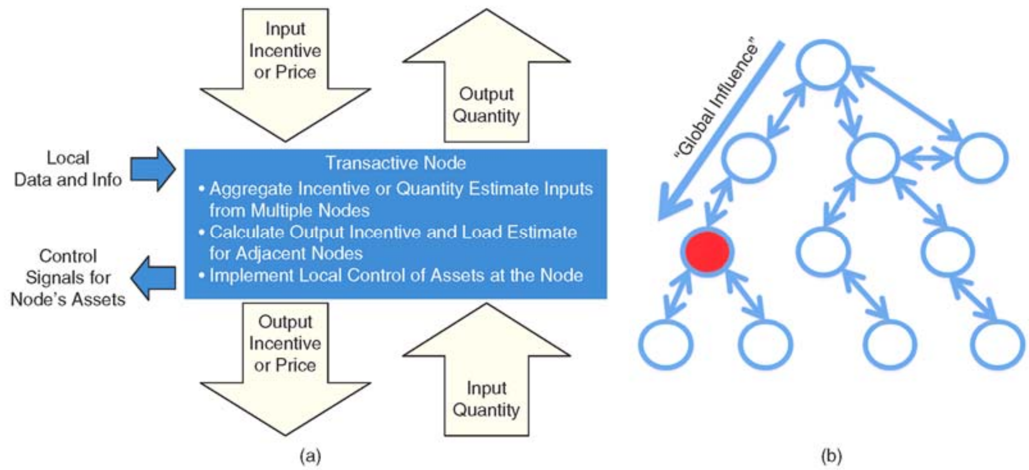

Figure 8. Overview of Transactive-Node Approach in the PNWSGD Project, including (a) the Node's Responsibilities and (b) the Node's Possible Location (Marked Red) and Communication among a Network of other Nodes

The core of the PNWSGD transactions is the TIS, which could be unique for each transactive node, because it is directly influenced by the node's components, such as energy suppliers, upstream (toward bulk generation) transmission pathways and distances, operational practices, local infrastructure, and downstream customers. Within one time interval n, the TIS is obtained as a weighted sum of all the incurred costs, whether production, capacity, infrastructure, or maintenance. Weights are given by the inverse of the entire load (including exported energy), or the entire supply (including the imports), at one transactive node:

$$TIS_n = \frac{energy\ costs + capacity\ costs + other\ costs}{total\ energy\ resources} + offset\ costs,$$

where the offset costs are the incentive functions that do not represent an energy resource.

The TFS is determined by each transactive node on a radial distribution branch by summing the inelastic/unresponsive loads and elastic/responsive loads to predict the power flow between it and its transactive neighbors. Each transactive node has a set of transactive neighbors to which it is electrically connected. These neighbors are also part of the transactive system, and agree to exchange energy unit cost (TIS) and energy quantity (TFS) with all their transactive neighbors. Each transactive node is required to exchange the information bidirectionally. This means that it will both send and receive both signals. Depending on the sign of the TFS, the energy exchanged between two neighboring transactive nodes could be considered an available resource or a load that needs to be supplied to the transactive node. Moreover, a transactive node might have its own electricity resources, and a responsibility to supply local loads.

In the case of local generation resources, an optimizer at the level of each transactive node has specific functions designed to monetize resource costs and incentives, while responding to the transactive node's attempts to balance supply and demand, especially as the loads respond to the TIS.

Much of the system load is inelastic, and thus unresponsive to the TIS. These loads need to be served by functions that accurately predict their behavior and energy consumption, because they have a big impact on the energy balance at the level of the transactive node, as well as the entire transactive system. The elastic or responsive loads' functions have a harder mission. First, based on the TIS and the local conditions, the timing and magnitude of elastic loads is to be determined, such as event-driven, daily, or continuous response. A second function is in charge of maintaining a performance model, which could help estimate and predict the impact of the elastic loads' response.

This innovative transactive methodology developed specifically for the PNWSGD coordinated DERs and demand-responsive assets. Not only has it proved that generation-driven operation of the grid is efficient and reliable for supply-demand balancing, it also addressed regional goals, such as mitigation of renewable energy intermittency and the flattening of system loads.

2.5 Transactive Campus Energy Systems

The transactive campus project is currently funded by Washington State's Clean Energy Fund (WA-CEF). WA-CEF was established as a source of matching capital investments in the state's research and development (R&D) infrastructure for federally funded R&D projects. This ongoing project proposes to connect the Pacific Northwest National Laboratory (PNNL), University of Washington, and Washington State University campuses to form a multi-campus testbed, as shown in Figure 9, for transactive energy management solutions. Building on the foundational transactive energy management system of the PNWSGD project, it proposes to construct and operate the testbed as both a regional flexibility resource and as an R&D platform for building and grid integration. Using the flexibility provided by loads, energy storage, and smart inverters for batteries and photovoltaic solar systems, the testbed will support the integration of renewables and other regional needs at four physical scales: multi-campus, campus, microgrid, and building. Each campus testbed will further be specialized as a platform on which additional R&D will be conducted to advance the state of knowledge in areas of critical interest to the project's U.S. Department of Energy sponsors.

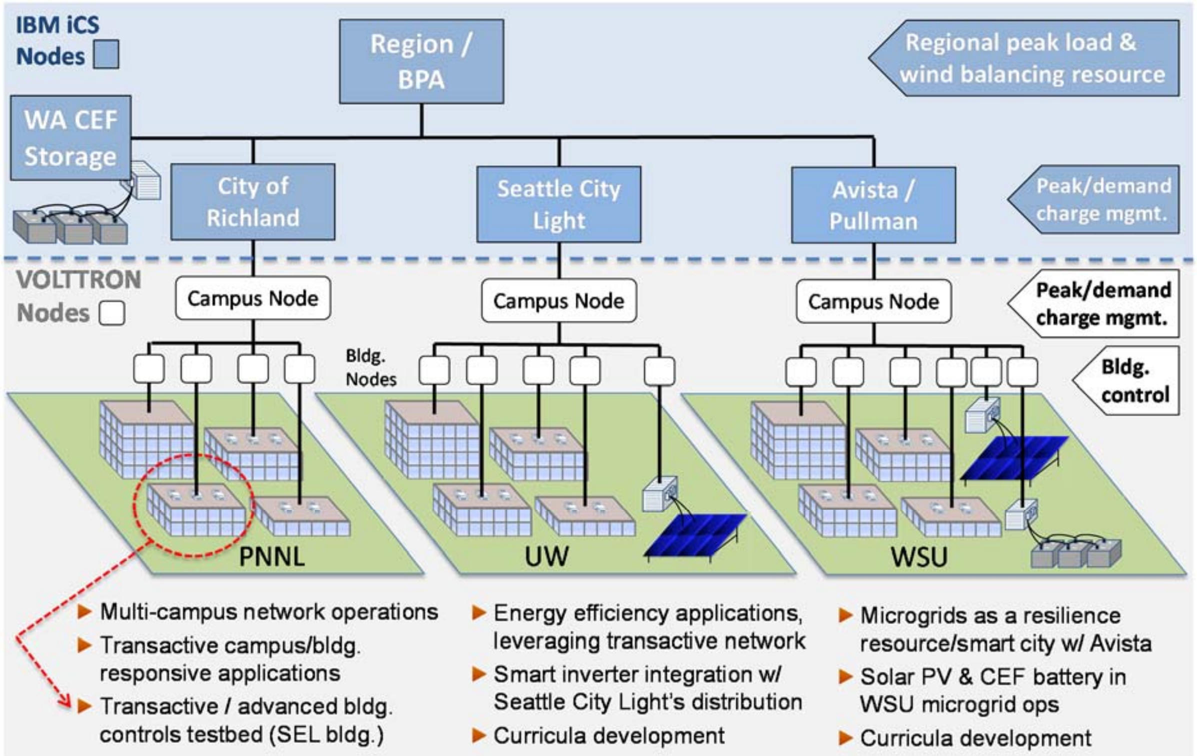

Figure 9. Multi-Campus Testbed in the Transactive Campus Project

PNNL has conducted additional R&D on transactive energy management systems for campuses and commercial buildings. The goal is to apply transactive energy concepts to control components within a commercial building as well as allow different buildings on a campus to trade and negotiate their energy consumption. In particular, a transactive approach was recently proposed to control the HVAC systems within commercial buildings for demand response. The technical details have been summarized in (Hao et al. 2016), and a sketch of the building system under transactive control is shown in Figure 10. Under the proposed transactive building control, air-handling units (AHUs) will "purchase" hot and cold water from the boiler and chiller, and "sell" heated and cooled supply air to the variable air volume boxes connected to the conditioned zones. A double-auction market will be constructed to efficiently coordinate various components of the HVAC system (AHUs, chiller, boiler, variable air volume boxes, etc.) through a market bidding and clearing process. This transactive approach is similar to the one used in the Olympic Peninsula, AEP gridSMART® and PowerMatching City demonstration projects. At the beginning of each market cycle, individual components first calculate local demand for the coming market period, and submit it to the central market along with an expected price. Then, the central market agent collects all the bids and clears the market to determine the clearing prices. The clearing prices for individual components are broadcast back to them. Finally, local controllers will translate the received clearing prices into the corresponding local inputs for the operation of individual components. Currently, this transactive building control approach is applied to the individual components of the energy systems within PNNL's newly constructed systems engineering building to realize reduced energy use and cost and allow for increased flexibility in managing demand.

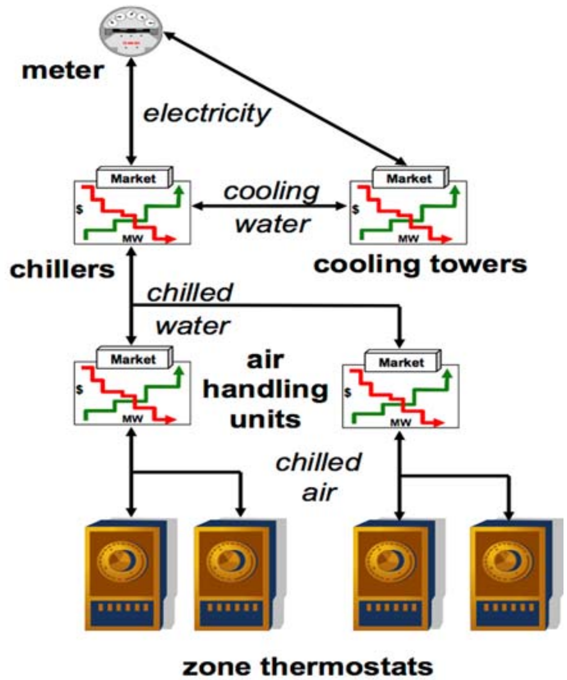

Figure 10. Conceptual Topology of Transactive Building Control

2.6 Transactive Energy Market Information Exchange

Transactive Energy Market Information Exchange (TeMix) is a transactive energy platform (Cazalet 2010) that allows different parties such as generators, DERs, and storage to transact with each other using a protocol network. The TeMix approach is a peer-to-peer transactive energy technique that allows exchange between unconnected neighbors, in contrast with the consensus technique used in the PNWSGD. The objective is to balance supply and demand using bilateral market instruments including derivatives. The customers and suppliers are engaged in decentralized markets for energy transactions that are binding exchanges of currency for a quantity of an energy product. The two basic energy products are (1) energy delivered at a specific location during a specific period of time, and (2) transport of energy from one location to another. The call options on energy or transport are comparable to the capacity and ancillary service products. In TeMix, forward contracts and real-time balancing services with varying prices are offered to the customers. Contracts may be traded at any time when there is a market. With an offer in the network, a counterpart will respond, and both parties enter into a binding commitment to transact at a specific price and location. Each participant needs to use their available resources or tools to enter into bilateral agreements. Supply and demand are balanced using financial instruments such as derivatives.

3.0 Overview of Microeconomic Theory

Transactive systems, even ones that appear at first to be dissimilar, derive from shared economic principles. Transactive energy can be broadly viewed as a class of methods that employ economic principles, concepts, and perspectives to study the coordination and control of energy resources that belong to stakeholders or users. Therefore, microeconomics plays a central role in the design and analysis of transactive energy systems.

This section provides a concise introduction to important concepts and results in microeconomic theory (Mas-Colell et al. 1995, Varian 1992). We will emphasize the important concepts and results that can be potentially applied to transactive energy systems.

Economic analysis typically involves the following four components:

(i) Economic environment: specify the key players, their characteristics, information structure, and basic environment setups, such as the exogenous variables and parameters.

(ii) Individual agent behavior models: describe how individual agents make economic decisions. This typically involves agents' preferences, rationality assumptions, information available to the agents, and their optimization problems.

(iii) Institutional arrangement: specify the rules in which agents interact with each other. These interaction rules couple individual decisions in specific ways, such as through a competitive market, an oligopolistic market, a particular auction setup, or a certain contract.

(iv) Outcome of the economy: define the outcome of the economy under study. Depending on the application and the setup of the previous components, the outcome can be a market equilibrium, a competitive equilibrium, a constrained competitive equilibrium, a Nash equilibrium, or a Bayesian Nash equilibrium, among others.

Depending on the application, one may study different properties of the given economy, such as efficiency, fairness, individual rationality, incentive compatibility, etc. A more challenging question is how to design an economic environment to induce an outcome to achieve a given desired social objective. Such a problem is called economic design. Economic analysis is the foundation for economic design. In the following, we will discuss several important paradigms for economic analysis and design. For each paradigm, we will first specify each of the four key components mentioned above and then present the main results.

3.1 Classical Welfare Economics

A competitive market is a key concept in microeconomic theory. The theoretical tools for analysis of competitive market economies also are fundamental to the study of other types of market mechanisms. The main results consist of a number of welfare theorems that are regarded as important cornerstones of microeconomics. The results can be presented in an exchange economy or the more general production economy using either a partial equilibrium approach or a general equilibrium approach.

For simplicity, we will present classical welfare economic results through an exchange economy using the general equilibrium approach. These classical welfare economic results cannot be directly used to analyze and design transactive energy systems. However, they are still arguably the most important economic results for transactive energy systems. In fact, most of the transactive energy examples presented in the previous section can be viewed as competitive market design problems to efficiently allocate energy or services to economic agents. The economic results reviewed in this section will explain important economic concepts that will serve as the foundation for developing transactive energy systems.

3.1.1 Economic Environment

The economic environment for an exchange economy usually consists of the following components:

- $\boldsymbol{N} = \{1, \ldots, N\}$: set of consumers
- $\boldsymbol{L} = \{1, \ldots, L\}$: set of private goods (commodities)
- $\boldsymbol{X_i} \subseteq \mathbb{R}^L$: consumption space of consumer $i \in \boldsymbol{N}$, specifying the boundaries of the consumptions over all the private goods. A vector $x_i \in X_i$ is called a (feasible) consumption vector
- $w_i \in \boldsymbol{X_i}$: initial endowment vector of consumer i
- $\boldsymbol{X} = \boldsymbol{X_1} \times \boldsymbol{X_2} \times \cdots \times \boldsymbol{X_N}$: overall consumption space. An element $x \in \boldsymbol{X}$, is called a consumption bundle.

3.1.2 Institutional Arrangement

Welfare economics is based on a private market mechanism, by which all the agents' decisions are coupled through a competitive market.

- $\lambda = [\lambda^1, \ldots, \lambda^L]^T \in \mathbb{R}_+^L$: a price vector
- $\lambda^T x_i$: the expenditure of consumer i
- $\lambda^T w_i$: the value of the endowments of consumer i.

3.1.3 Individual Decision Model

An exchange economy only involves one type of players, namely, the consumers. Their decision process is described below.

- Each consumer $i \in \boldsymbol{N}$, has a known preference for each of the L goods. It is typically assumed that such preference can be captured by a utility function $U_i(x_i)$ that depends only on the consumption of agent i, i.e., there is no externality.
- In the given perfect competitive market, each agent i is assumed to be a price-taker and determines her consumption by solving the following utility maximization problem:

$$\begin{cases} \max_{x_i} U_i(x_i) \\ \text{subject to } \begin{cases} x_i \in \boldsymbol{X_i} \\ \lambda^T x_i \leq \lambda^T w_i \end{cases} \end{cases}$$

In this problem, the first constraint is called the individual feasibility constraint while the second constraint is the agent's budget constraint. The overall constraint set depends on the price vector and will be denoted by

$$B_i(\lambda) = \{x_i \in X_i : \lambda^T x_i \leq \lambda^T w_i\}.$$

3.1.4 Economic Outcome

The outcome (competitive equilibrium) of a competitive market in the exchange economy is a price-allocation pair (λ, x). An allocation profile $x = (x_1, \dots, x_N)$ specifies what goods and how much each agent holds. A desired allocation needs to satisfy some conditions or desired properties.

Definition – Feasible Allocation: An allocation $x = (x_1, \dots, x_N)$ is called *feasible* if $x_i \in \boldsymbol{X_i}$, for all $i \in \boldsymbol{N}$, and $\sum_{i=1}^{N} x_i = \sum_{i=1}^{N} w_i$

An essential requirement for a feasible allocation profile to be optimal is that it possesses the so called Pareto optimality (or Pareto efficiency) property.

Definition – Pareto Efficiency: An allocation $x = (x_1, \dots, x_N)$ is called Pareto efficient (or Pareto optimal) if it is feasible and there is no other feasible allocation that is strictly preferred by all the agents, i.e., there is **no other feasible** $\hat{x} = (\hat{x}_1, \dots, \hat{x}_N)$ such that $U_i(\hat{x}_i) \geq U_i(x_i), \forall i \in \boldsymbol{N}$ and $U_j(\hat{x}_j) > U_j(\hat{x}_j)$ for some $j \in \boldsymbol{N}$**.**

Note that in the above definitions, individual budget constraints are not considered.

In a competitive market, each price vector λ will induce an allocation profile x through individual utility maximizations. A price-allocation pair (λ^*, x^*) is called a competitive equilibrium if every agent's consumption x_i^* is the best response for the given price λ^*.

Definition – Competitive (Walrasian) Equilibrium: An allocation profile $x^* = (x_1^*, \dots, x_N^*)$ and a price vector λ^* is called a competitive equilibrium if the x^* is feasible and satisfies

$$U_i(x_i^*) \geq U_i(x_i), \text{ for all } x_i \in B_i(\lambda^*) \text{ and for all } i \in \boldsymbol{N}.$$

3.1.5 Fundamental Welfare Theorems

Classical welfare economic theory is mainly concerned with the efficiency of the allocation, i.e., whether there is unnecessary waste of resources in the society. The key questions the theory tries to answer are whether an equilibrium of a competitive market is Pareto efficient, and under what conditions a given Pareto efficient allocation can be achieved induced by a competitive market. The main results are two fundamental welfare theorems stated below.

First Fundamental Welfare Theorem: If (x^*, λ^*) is a competitive (Walrasian) equilibrium, then x^* is Pareto efficient.

Second Fundamental Welfare Theorem: Suppose that x^* is Pareto optimal and the utility functions are concave, continuous, and monotonic. Then there exists a price vector λ^* such that (x^*, λ^*) is a competitive equilibrium with initial endowment $w_i = x_i^*$.

Pareto efficiency is only concerned with efficiency and does not specify how to allocate the welfare to different agents. Given an (exchange) economy, there are typically infinitely many Pareto efficient allocations. One way to specify the distribution is by introducing a social welfare function.

Definition – Social Welfare Function: A function $W: R^n \rightarrow R$ is called a welfare function for N economic agents if W is monotonically increasing in each of its arguments.

In this context, we assume that the society should operate at a point that maximizes social welfare defined by W, that is, we should choose an allocation x^* that solves the following social welfare optimization problem:

$$\begin{cases} \max_{x \in X} W\big(u_1(x_1), \dots, u_N(x_N)\big) \\ \displaystyle\sum_{i=1}^{N} x_i \le \sum_{i}^{N} w_i \end{cases}$$

Theorem – Welfare Maximization → Pareto Efficiency: If x^* maximizes a social welfare function, then x^* is Pareto efficient.

Theorem – Pareto Efficiency → Welfare Maximization: Let x^* be a Pareto efficient allocation with $x_i^* > 0$ for all $i \in \boldsymbol{N}$. Assume that each utitliy function u_i is concave, continuous, and monotonic. Then there exist nonnegative weights a_i with $\sum a_i = 1$ such that x^* is the solution to the social welfare maximization problem with welfare function $W = \sum_i^N a_i u_i(x_i)$.

The theorems presented in this section are not stated in the most general form. Generally, the main results in classical welfare theory can be summarized as follows:

- Competitive equilibrium is Pareto efficient.
- Pareto efficient allocations can be obtained through competitive equilibria under concavity assumptions and endowment redistributions.
- Social welfare maxima are Pareto efficient.
- Pareto efficient allocations are welfare maxima under concavity assumptions for some choice of welfare weights.

3.2 Information Economics

A competitive market is arguably the most important economic paradigm for transactive energy systems, especially when the system involves a large number of participants. Nonetheless, there are cases under which a transactive energy system cannot be modeled as a competitive market. For example, when the number of participants is small, the price-taker assumptions are no longer appropriate. In such cases, one may consider using monopolistic or oligopolistic markets to analyze the system outcome. Although the analysis will be quite different for these cases, they follow similar ideas. A more dramatic difference will occur if we adopt a different information structure assumption. For competitive/monopolistic/oligopolistic markets, we assume every agent has complete information about the whole economy system. However, in reality, much information is privately held by agents, and some agents are more informed than others. The asymmetry of information will completely change the nature of economic analysis and design. The study of economic systems under asymmetric information is often called information economics, another focus of modern microeconomic theory (Borgers et al. 2015, Diamantaras et al. 2009, Krishna 2009, Laffont and Martimort 2009, Vohra 2011).

4.0 Theoretical Foundation for Transactive Energy Systems

Transactive energy systems can be viewed as a class of special economic-engineering systems. Studying this class of systems requires the development of specialized economic foundations and principles that could be quite different from the classical economic results. The development of transactive coordination and control involves the design of appropriate market rules to engage and coordinate various DERs such as energy storage, distributed generation, and responsive end-user loads to achieve certain group objectives while respecting local objectives and constraints. This coordination and control problem can be studied from many different perspectives at different levels. At the resource level, we can consider the problem of individual or aggregated resource modeling. We can also consider how individual resources make decisions under the given market structure. At the coordination level, we can consider how the coordinator makes decisions in the given market structure. We can also consider a more challenging problem of how to design appropriate market rules. Designing transactive energy systems poses two major challenges. One challenge is imposed by the resource modeling. We have to model not only the resource dynamics but also their economic preferences. The other challenge arises from the computational issues. Many principles and concepts that are clear in microeconomic theory may be difficult to implement computationally. For example, it would be almost impossible to compute the Nash equilibrium of a game even when the microeconomic theory proves its existence. This has been known in general as an "NP-hard" problem. Therefore, appropriate mathematical tools should be applied to practical problems. In this section, we will examine the economic foundation of transactive energy systems to illustrate the underlying design challenges. We will develop a theoretical foundation with a formal specification of the essential economic assumptions and components of a general transactive energy system, and those existing economic results will be leveraged and extended to solve transactive energy problems.

4.1 Transactive Control Framework

In order to apply transactive approaches to coordinate and control DERs, we first need to model these controllable resources, their decision making, and the market interactions among their decisions. For this purpose, we propose a theoretical transactive control framework that consists of four key elements: payoff functions, control decisions, information, and the solution concept. We will present the details of these elements in the following subsection.

4.1.1 Payoff Functions

Consider the case with one coordinator and N control DERs (or agents). Throughout this section, we refer to the coordinator as agent 0 and others as agent i. In general, individual controllable resources are modeled as automated agents that can communicate with other agents and the coordinator and perform local decision making. They seek only to maximize their own local payoff when interacting with others and the system coordinator. This local objective can be represented as a payoff function that depends on the energy consumption of the resource and the price. In this case, each agent wants to maximize his payoff subject to local constraint. For each agent $i = 1, \ldots, N$, we can formulate the payoff maximization problem as follows:

$$\underset{p_i}{\text{Maximize}} \quad V_i(p_i, \lambda_i; \theta_i) \tag{1}$$

$$\text{Subject to} \quad h_i(p_i; \theta_i) \le 0,$$

where $V_i(p_i, \lambda_i; \theta_i)$ is the payoff function of each controllable load for its energy consumption p_i under the energy price λ_i, and θ_i is private information including agent preferences and local constraints. Notice that the optimization variable is unstated, since we have not yet specified the control decision of each agent yet. This will be clear after we introduce the control decision later.

For the coordinator, we can define a similar payoff maximization problem subject to constraints:

$$\underset{p_i}{\text{Maximize}} \quad V_0(p, \lambda; \theta) \tag{2}$$

$$\text{Subject to} \quad g(p, \lambda; \theta) \le 0$$

$$h_i(p_i; \theta_i) \le 0,$$

where $p = (p_1, \dots, p_N)$, $\lambda = (\lambda_1, \dots, \lambda_N)$, $\theta = (\theta_1, \dots, \theta_N)$ and $V_0(p, \lambda; \theta)$ is the payoff function of the coordinator. Unlike DERs, the coordinator's objective function depends on the energy consumption and prices of all DERs. In addition, he also has a global constraint to maintain, such as the power flow constraint of the transmission system.

This optimization problem in (1) and (2) can cover a single period or multiple periods, depending on whether the energy consumption is defined over a period of time. The local constraints are usually expressed in terms of capacity and ramping limits. These limits are determined simultaneously based on the local dynamics, control strategies, and operating ranges. For example, the feasible energy consumption of an air conditioning unit during a period is constrained by the current room temperature with respect to the comfort zone specified by the consumer and how fast the room temperature can be changed. There are several difficulties in modeling DERs. First, it is difficult to accurately model some controllable resources such as residential HVAC units, which have very complicated characteristics and dynamics in power system applications. Second, it is difficult to obtain the utility function of controllable loads. Unlike the cost function of controllable generators, which can be easily determined based on generator operational cost, fuel efficiency, and fuel cost, the utility function should be determined by the underlying economics of energy consumption. However, extracting the underlying economics based on the preferences of individual customers is not straightforward. Furthermore, the economic preferences should affect local dynamics in certain ways, which makes the resource modeling even more challenging. Therefore, there is no universal model for all applications with all types of DERs.

4.1.2 Control Decisions

The payoff function specifies what objective each agent wants to optimize, but it does not specify how each agent optimizes its objective. This can be done by defining a set of control decisions for the coordinator and DERs.

Let $\gamma_i \in \Gamma_i$ be the decisions of agent i, and let $\gamma_0 \in \Gamma_0$ denote the control decision of the coordinator. In this case, Γ_i and Γ_0 are the feasible control decisions for the agents and the coordinator, respectively. We allow the control decisions to have different forms, as long as the energy and price (e, p) are uniquely determined whenever the decisions of all participating entities are given. Below we give an example.

Consider the case where the coordinator determines the unit price of energy, and each agent determines its own energy consumption. In other words, we can write the decisions as $\gamma_0 = p$ and $\gamma_i = e_i$. In this case, the optimization problem is

$$\begin{aligned} \underset{\gamma_i}{\text{Maximize}} \quad & V_i(\gamma_i, \gamma_0; \theta_i) \\ \text{Subject to} \quad & h_i(\gamma_i; \theta_i) \leq 0, \end{aligned} \tag{3}$$

and the coordinator's payoff optimization problem becomes

$$\begin{aligned} \underset{\gamma_0}{\text{Maximize}} \quad & V_0(\gamma_0, \gamma_1, \dots, \gamma_N; \theta) \\ \text{Subject to} \quad & g(\gamma_0, \gamma_1, \dots, \gamma_N; \theta) \leq 0 \\ & h_i(\gamma_i; \theta_i) \leq 0. \end{aligned} \tag{4}$$

It is important to note that after the control decision is specified, the payoff functions can be written as the function on the decisions $(\gamma_0, \gamma_1, \dots, \gamma_N)$, and unlike the original problem (1), the induced problem (3) introduces coupling between the decisions of different agents. In the case of (3), the payoff of the agents depends not only on their own decisions, but also on that of the coordinator. Note that in a more general case, the decision variable may not be price, and the agent decision may not be its energy consumption. For instance, the coordinator may need to determine a pricing function that maps the energy consumption to a price. In such case, the utility of each agent not only depends on his decision and the coordinator's decision, but can also depend on the decisions of other agents.

4.1.3 Information

Aside from control decisions, the information availability to each agent in the system is also an important element of transactive energy systems. To capture the information structure of the system, we define an information set for each agent as I_i, and define an information set for the coordinator as I_0.

The information set consists of two parts. The first part describes the private information of the agents, denoted by I_i^t, which can be user preferences or local constraints. In the transactive control framework, it is important to specify whether each agent or coordinator knows the preferences or local constraints of others. In different cases, the techniques employed to solve the problem can be significantly different. The second part of the information set concerns the information on control decisions of each agent or the coordinator, denoted as I_i^c. More specifically, it describes whether an agent or coordinator knows the control decisions of others before he makes his own decision. If agent i knows the decision of agent j before he moves, then we write $\gamma_j \in I_i^c$.

As an example, consider an information set $I_i = \{I_i^t, I_i^c\}$, where each agent i knows its own private information, but does not know the information of others. In this case, $I_i^t = \{\theta_i\}$. In addition, the coordinator does not know the private information of the agents, but only knows a prior probability distribution on θ, denoted as $F(\theta)$. Therefore we have $I_0^t = F(\theta)$. In this example, let the coordinator determine the price first and announce the price to each agent. Then we have $I_0^c = \emptyset$ and $I_i^t = \gamma_0$.

Note that the information on control decisions inherently indicates a sequence of decisions. For instance, if the agent knows the coordinator decision before he moves, then it indicates that the coordinator moves first, and then the agent moves accordingly. In general, we allow any information structure that may lead to any sequence of actions. For instance, the coordinator and some agents may make decisions first, then these decisions are passed down to the rest to make their decisions accordingly. This sequential decision can be illustrated as in Figure 11.

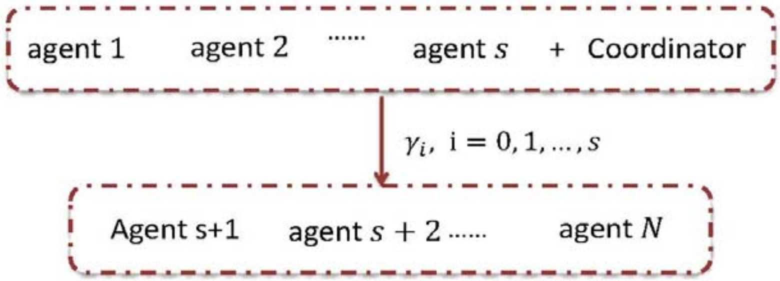

Figure 11. Sequential Decision Making

4.1.4 Solution Concept

The information on control decisions provides a sequence of decisions among the agents and the coordinator. This leads to a multilevel decision problem. Note that at each level of the problem, the agents move simultaneously. Therefore, in general the multilevel problem can be viewed as multiple layers of problems. The entire population of agents is divided into several layers, and those in the same layer make control decisions simultaneously.

The key remaining concern is that within each layer, the simultaneous-move problem may be coupled. In other words, the payoff functions of the agents in any layer may depend on the decisions of other players in the same layer. Therefore, each layer may be a simultaneous-move game problem, and a proper solution concept must be selected for each layer of the problem. Note that in our context, the solution concept refers to the solution for each layer. The overall transactive control problem may have different layers, and may have different solution concepts for different layers.

Now consider an arbitrary layer, and assume there are s agents in this layer. To define the solution concept, there are two different cases.

(1) When the payoff function of each agent does not depend on the decisions of other players in this layer, then the solution concept is simply the optimal solution to a standard optimization problem. For instance, in this case we can write the payoff function as $V_i(\gamma_i)$, and the solution γ_i^* simply satisfies $\gamma_i^* = \underset{\gamma_i}{\operatorname{argmax}} V_i(\gamma_i)$.

(2) When the payoff function of each agent depends on the other agents in the same layer, then we have a game problem, and the solution to this problem is a game equilibrium. There are two basic versions of solution concept for a game problem: Nash equilibrium and the dominant strategy equilibrium, which are described below.

Nash equilibrium in our context is a collection of decisions from which no one wants to deviate given that others stick to the equilibrium decision. Mathematically, we can define the Nash equilibrium as follows:

Definition – Nash equilibrium: a collection of strategies $\gamma^* = (\gamma_1^*, \dots, \gamma_s^*)$ is a Nash equilibrium for the simultaneous-move game problem if for each $i = 1, \dots, s$, we have

$$V_i(\gamma_i^*, \gamma_{-i}^*) \geq V_i(\gamma_i, \gamma_{-i}^*)$$

for all γ_i, where γ_{-i} denotes the decisions of all players in this layer other than that of agent i, i.e., $\gamma_{-i} = (\gamma_1, \dots, \gamma_{i-1}, \gamma_{i+1}, \dots, \gamma_s)$. In Nash equilibrium, the agent has no motivation to deviate from the equilibrium strategy only if others commit to the equilibrium strategy. If the other players do not commit to the equilibrium strategy, he may want to reconsider his control decision.

In contrast, the dominant strategy equilibrium is more stable in the sense that each agent will stick to the equilibrium strategy no matter what decisions other players make. Formally, we can define it as follows:

Definition – dominant strategy equilibrium: a collection of strategies $\gamma^* = (\gamma_1^*, \dots, \gamma_s^*)$ is is a dominant strategy equilibrium for the simultaneous-move game problem if for each $i = 1, \dots, s$, we have

$$V_i(\gamma_i^*, \gamma_{-i}) \geq V_i(\gamma_i, \gamma_{-i})$$

for all γ_i and all γ_{-i}.

4.2 Realizations of Transactive Control Framework

The proposed framework can be used to recognize the similarities and differences among different types of transactive energy systems, and identify the key challenges in each type. In the remainder of this section, we will apply the proposed framework to study some important transactive energy systems in the literature.

4.2.1 Centralized Optimization

If the coordinator knows all the information about the agents, such as their cost and utility functions, the resource allocation problem can be solved directly as a centralized optimization problem. In this case, the control decision of the coordinator is the energy allocation to each agent and the energy price, and the agent does not make any decisions. The coordinator will first collect the cost and utility functions from individual resources. Because most of the resources are nonstrategic, the collected information will be truthful. The coordinator then solves the global optimization problem to obtain the optimal energy allocation, and dispatches the individual resources to follow the allocated amount of energy. In many cases, the global optimization problem is convex, and thus the solution can be easily determined. However, including the load dynamics in the optimization problem makes the problem very challenging to solve. Some related work can be found in (Kohansal and Mohsenian-Rad 2016, Mohsenian-Rad et al. 2010, Yang et al. 2014).

4.2.2 Competitive Market

A very important class of transactive problems is one where the agent's objective function is quasi-linear with respect to the price, and the coordinator's objective is to minimize the overall operational cost while engaging DERs to balance supply and demand and provide ancillary services. More specifically, this agent payoff function is $V_i(p_i, \lambda; \theta_i) = U_i(p_i; \theta_i) - \lambda_i p_i$, where $U_i(p_i)$ denotes the agent's utility resulting from consuming the energy p_i, and the term $\lambda_i p_i$ is the energy payment. Given the agent's objective function, the global objective can be formulated as a social welfare maximization problem:

$$\underset{\gamma_i}{\text{Maximize}} \quad \sum_{i=1}^{N} U_i(p_i;\theta_i) - C\left(\sum_{i=1}^{N} p_i\right) \tag{5}$$

$$\text{Subject to} \quad g(p,\lambda;\theta) \le 0 \text{ (Global constraints)}$$

$$h_i(p_i;\theta_i) \le 0, \text{ (Local constraints)}$$

where $U_i(p_i;\theta_i)$ is the utility function of each DER, and $C(\cdot)$ is the cost function of energy consumption. The objective function is defined as the difference between total utility and total cost of energy. The global constraints include constraints imposed on power balance, line flow, voltage magnitude, system reserve limits, etc. The local constraints are capacity and ramping limits for the individual resources.

Next we show that the competitive market is a special case of the proposed transactive control problem. Since we have already specified the payoff functions of the agent and the coordinator, it suffices to define the control decision, the information set, and the solution concept. In this case, the control decision of the agent is its energy consumption and the coordinator's decision is price. Therefore, we have $\gamma_0 = \lambda$ and $\gamma_i = p_i$. In terms of the information, the coordinator does not know the private information of the agents, and he determines the price first. In addition, since the agent decisions are decoupled after the price is given, the solution concept is the standard solution to optimization problems. We comment that the competitive market problem typically collects information before implementing the solution. In this step, it assumes the agents to be price-takers, and thus each agent will report truthful information. In this regard, although the coordinator does not know the private information in the original setup, it is essentially equivalent to the case where all private information is known.

There are different ways of computing the solution of the competitive market. Broadly speaking, these methods can be characterized into two different types according to whether an iterative algorithm is needed in computing the solution.

(1) One method is the non-iteration–based algorithm. It typically requires the agent to submit a demand curve. Based on the submitted bids, the coordinator constructs aggregated demand and supply curves. The market is then cleared at the intersection of the two curves. It can be shown that the solution of such method maximizes the social welfare (Hao et al. 2017, Li et al. 2016).

(2) The second method is to use iterative algorithms. These algorithms can be divided into several categories, such as primal-dual algorithms (Chen et al. 2012, Chen et al. 2010b, Gan et al. 2013, Hansen et al. 2015, Jokic et al. 2010, Li et al. 2011b, Mohsenian-Rad et al. 2010, Nguyen et al. 2012, Papadaskalopoulos and Strbac 2013), average consensus algorithms (Zhang and Chow 2011, Zhang and Chow 2012a, Zhang and Chow 2012b), ratio consensus algorithms (Dominguez-Garcia et al. 2012, Yang et al. 2016), etc.

For example, consider a social welfare maximization problem (5) with a global constraint that requires power balance. When it is a convex optimization problem, we can solve it via dual decomposition. At each iteration, individual resources first solve the local optimization problem as specified by the coordinator, then communicate with their neighboring resources according to predefined protocols to determine the power imbalance, and finally update the dual variable locally. This process iterates until the dual variables converge to the same value. The primal-dual algorithm for this problem can be summarized as follows:

(1) At the k-th iteration, solve the primal subproblem: $p_i = \underset{p_i}{\text{argmin}}\, U_i(p_i; \theta_i) - \lambda(k)p_i$;

(2) Update the dual variable λ as $\lambda(k+1) = \lambda(k) - \gamma\Delta p(k)$, where $\Delta p(k) = \sum_{i=1}^{N} p_i\,(k) - D$.

4.2.3 Stackelberg Game

The coordination problem becomes more challenging to solve when the individual payoff function is not quasi-linear, and the coordinator's objective is different from maximizing the social welfare. In this case, the problem becomes a Stackelberg game (Basar and Srikant 2002, Coogan et al. 2013, Jiang and Low 2011, Maharjan et al. 2013, Stankova and De Schutter 2011, Tushar et al. 2014, Tushar et al. 2012, Tushar et al. 2014, Yang et al. 2015, Zhong et al. 2013). We will formally discuss the four elements corresponding to Stackelberg game.

The first important difference between a competitive market and the Stackelberg game lies in the payoff functions of the agents and the coordinator. In the Stackelberg game, the individual agent payoff function can be a general concave function of the energy consumption and the unit price, i.e., $V_i(p_i, \lambda_i; \theta_i)$. Typically it is assumed that the marginal benefit of consuming a unit of energy is decreasing; this leads to a concave function V_i with respect to e_i. Also, the coordinator's objective is not necessarily to maximize the social welfare. For instance, it may want to maximize its profit by selling energy to the individual agents. In the Stackelberg game, we let the agent's control decision to be its energy consumption, and let the coordinator's control decision be the energy price. This is the same as in the competitive market case. In terms of information, we assume that the coordinator knows all the private information of the agents, and it acts first. This is different from a competitive market, where the coordinator does not know the private information of the individual agents. In addition, in Stackelberg games, the lower level problem may be coupled or not, and the solution concept should be defined accordingly.

For example, if the coordinator's objective is to maximize his profit, then the optimization problem of the coordinator is defined as

$$\begin{aligned} \underset{\gamma_i}{\text{Maximize}} \quad & \lambda \sum_{i=1}^{N} p_i - C\left(\sum_{i=1}^{N} p_i\right) \\ \text{Subject to} \quad & g(p, \lambda; \theta) \le 0 \\ & h_i(p_i; \theta_i) \le 0, \end{aligned} \tag{6}$$

and the optimization problems of individual agents are defined as

$$\begin{aligned} \underset{\gamma_i}{\text{Maximize}} \quad & U_i(p_i, \lambda; \theta_i) - \lambda p_i \\ \text{Subject to} \quad & h_i(p_i; \theta_i) \le 0. \end{aligned} \tag{7}$$

This is referred to as the Stackelberg game, and the solution satisfies the following optimization problem:

$$\begin{aligned}
\underset{\gamma_i}{\text{Maximize}} \quad & \lambda \sum_{i=1}^{N} p_i - C\left(\sum_{i=1}^{N} p_i\right) \\
\text{Subject to} \quad & g(p, \lambda; \theta) \leq 0 \\
& h_i(p_i; \theta_i) \leq 0, \\
& p_i = \underset{h_i(p_i;\theta_i)\leq 0}{\operatorname{argmax}} \; U_i(p_i, \lambda; \theta_i) - \lambda p_i
\end{aligned} \tag{8}$$

The computation of the equilibrium of a Stackelberg game is typically very challenging (Colson et al. 2007). A special case is when the coordinator's objective function is linear with respect to λ and the agent's objective function is linear or quadratic with respect to e_i. In this case, the lower level problem is on the boundary of the constraint polytope, allowing efficient algorithms to solve the globally optimal solution. On the other hand, when the payoff function is not linear, one can try to solve the problem using well-developed numerical tools (such as KNITRO (Byrd et al. 2006)). However, in this case there is no guarantee that the solution is globally optimal, and the problem may be computationally intensive if the dimension is large.

4.2.4 Mechanism Design

When the coordinator does not have the full knowledge of the individual resources' private information and the resources are strategic, it is the most challenging case, and the concept of mechanism design from microeconomics must be adopted to solve this problem. In this case, the information exchange is realized by bidding and clearing. Each resource aims to maximize local payoff and strategically determines bidding information sent to the coordinator. The coordinator needs to incentivize individual resources to reveal the true information in their bids so that the global objective can be achieved without compromising local objectives; i.e., the coordinator influences individuals' decisions indirectly through pricing to achieve the desired social optimum.

Mathematically, the payoff functions of the mechanism design problem are similar to the Stackelberg game, where the coordinator and the agents can have general cost functions. However, the key difference between mechanism design and a Stackelberg game lies in the control decisions and the information. In mechanism design, each agent is asked to submit a bid; thus, the agent's decision is its bid. The coordinator then collects the bids from agents and determines the energy allocation and price. Therefore, the coordinator's decision is a mapping from the bids to an energy/price pair. Note that in the mechanism design problem, the coordinator needs to determine a market rule instead of a market price. This means the coordinator's decision is a function rather than a price value, which is different from the Stackelberg game. In terms of information, an important complication in mechanism design is that the coordinator does not know the private information of the agents. Thus his decision cannot depend on the private information, which is typically the case in a Stackelberg game. Since the individual preferences are unknown and the agents are strategic, they may not reveal their true preferences and may try to manipulate the price in order to increase their revenue. Therefore, the key challenge in mechanism design is for the coordinator to design a mechanism that motivates each agent to bid truthfully. When a mechanism induces truthful bidding, we say it is incentive compatible.

Mechanism design is extensively studied in economics, computer science, and various engineering fields. Papers related to mechanism design include (Athey and Segal 2013, Azevedo and Budish 2013, Bergemann and Välimäki 2010, Bitar and Xu 2013, Kearns et al. 2014, Li and Zhang 2015, Nissim et al. 2012, Pavan et al. 2014, Pavan et al. 2009, Samadi et al. 2012a, Xu et al. 2016). In (Forouzandehmehr et al. 2015, Gerding et al. 2011, Grammatico et al. 2015, Ma et al. 2013), Nash equilibriums are analyzed based on the given mechanisms. However, despite these efforts, there are still many challenges. For instance, in many engineering applications, the private information of the agents cannot be parameterized as a scalar, which limits the available techniques to solve the problem. In addition, in energy markets, we typically require the price to be the same for the agents at the same location, which is quite challenging for the purpose of mechanism design. Furthermore, many classical mechanism design approaches are computationally complex (Nisan et al. 2007). These results are hard to implement in large-dimension problems.

5.0 Conclusions

In this report, we first reviewed different transactive energy system designs that were deployed in several major demonstration projects in the U.S. and Europe. These demonstration projects have successfully proven the technical feasibility of transactive energy. In order to help understand the difference between these different transactive energy systems, it is important to establish the underlying theoretical foundation. We provided a concise introduction to important concepts and results in microeconomic theory. Then we developed a unified theoretical framework with a formal specification of the essential economic assumptions and components of a general transactive energy system. With the proposed theoretical framework, existing transactive energy systems can be rigorously analyzed, and future transactive energy systems can be systematically designed.

Our next step is to develop a set of performance metrics to compare the performance and identify the limitations of various transactive energy systems. Then we will apply the proposed theoretical framework to systematically analyze transactive energy systems deployed by the AEP gridSMART® demonstration project and the PNWSGD project.

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