Distribution System Controls Assessment in a Nonbinding Transactive Energy Market

Somayeh Moazeni
Stevens Institute of Technology
Hoboken, New Jersey 07030–5906
Email: smoazeni@stevens.edu

Boris Defourny
Lehigh University
Bethlehem, Pennsylvania 18015–1518
Email: defourny@lehigh.edu

***Abstract*—In a nonbinding transactive energy market with a distribution system operator (DSO) and a set of distributed flexible energy resources, this paper studies the DSO controls. In this framework, DSO sends discharge permission signals to a subset of enrolled transactive agents, who then have the option, but not the obligation, to discharge power in real time at a time-varying payoff specified in advance in the contract. The DSO controls include decisions on when to dispatch discharge permissions and which subset of transactive agents should be selected at a time to receive the permission to operate. Three schemes for transaction trigger policy and agent selection policy for this nonbinding transactive market are developed. In these schemes the real-time electricity prices and the difference between the real-time and day-ahead loads are employed. Using data from NYISO the intensity of discharge permissions for each transaction trigger policy is estimated. For a nonlinear payoff structure and assuming that the distributed agents all follow their optimal control policies, the value of the nonbinding transactive energy market for the flexible energy resources as well as for DSO is computed under each DSO control. It is shown that the transaction trigger policy, determined by positive unforecasted loads and real-time power prices greater than the contractual time-varying payoff parameter, outperforms other policies in terms of the achievable cost saving for DSO.**

***Index Terms*—Transactive energy, power market, distributed flexible energy resources, stochastic dynamic optimization.**

I. Introduction

Transactive energy markets involving distributed energy resources have been envisioned for the power grid of the future [1], [2], [3]. These energy markets aim to create opportunities for broader integration and participation of variable generations and those power system assets who cannot or do not want to enroll in the wholesale market. The expected characteristics of a transactive energy market in comparison with typical wholesale markets are summarized in Table I. While a power plant can take part in the day-ahead or real-time wholesale markets after accepting the compliance with the process requirements and commitments, transactive energy markets facilitate transactions by an electric vehicle or residential energy storage.

Quick ramping capabilities of flexible energy resources and improvements in their reliability and affordability ensure major roles for these technologies in transactive markets [4], [5]. Energy storage, plug-in hybrid electric vehicles, and demand response constitute prominent current and emerging technologies for flexible generations, see e.g. the US Department of Energy report [6].

TABLE I
Transactive Energy Market versus Wholesale Market

	Wholesale Market	Transactive Market
Grid Level	Transmission	Distribution
Profit Level	High	Low
Commitment Level	High	Low
Operation Time	Fixed	Flexible
Capacity Size	Large	Small

Creating an environment in which distributed flexible capacity resources can participate in the production and trading electricity, without dealing with the complexities and commitment requirements of the wholesale market, requires designing markets with appropriate features. In particular, such markets should accommodate the needs and limitations of all market participants, while maintaining the operability of the power grid. The lack of appropriate markets and business models has been identified as one of the main barrier in further deployment of energy storage (see e.g. [7] and Sandia National Laboratories report [8]), in spite of its emerging technological advances and cost improvements [9], [10].

While the importance of transactive energy and features of appropriate market models for distributed flexible capacities have been recognized in the recent few years (e.g., see [7]), research activities are still under development and specific market frameworks are scarce [1], [11].

In [12], an energy transaction framework is proposed for the deployment of energy storage or other resources with generation flexibility. In this paradigm, transactions are defined between these distributed flexible energy resources, referred to as *transactive agents*, and a *distribution system operator (DSO)* such as a power utility company. The two parties undergo an agreement based on which a transactive agent has the option, but not the obligation, to discharge power in real time, whenever DSO dispatches a discharge permission signal to this agent. Payoffs for the injected energy are time-varying and agreed upon in advance. A salient characteristic of this transactive market is its flexibility and nonbinding nature, in the sense that the transactive agents do not have to commit in advance to provide electricity, and the DSO does not commit to buying electricity at specific times in advance. In addition, the transactive agent does not need to undergo complex bidding processes. This comfort comes at the cost of uncertainty about times when electricity is permitted to flow out of the resource. The DSO dispatches operation permission signals to a subset of enrolled transactive agents at times, driven by the state of the grid or electricity price. Restricting operation times at which a participating transactive agent is allowed to discharge enables the DSO to indirectly supervise the activities of the distributed agents and control their effects on the power grid and market.

The control problem faced by a transactive agent enrolled in this market and its optimal discharge decisions are studied in [12]. Given the intensity rate of the operation permissions and the time-varying nonlinear payoff structure, the agent's control problem is reduced to a semi-Markov decision problem. An algorithmic strategy to solve this problem is proposed in [12], and properties of the optimal policy and value function are analyzed.

This paper investigates the nonbinding transactive market framework in [12] from the point of view of the DSO. The distribution system operator control includes decisions on when to dispatch discharge permissions and which subset of transactive agents should be permitted to operate. Two policies, referred to as the *transaction trigger policy* and the *agent selection policy*, are introduced. This paper proposes three transaction trigger policies and three agent selection policies, specified by the state of the real-time electricity price or unforecasted load as well as the payoffs to be paid to the agents. Using the real-time actual and day-ahead load data, and the real-time locational based marginal price (LBMP) data from Long Island (zone K) of New York Independent System Operator (NYISO) from Jan. 1, 2016 to Dec. 31, 2016, the arrival rates corresponding to each transaction trigger policy is estimated. Then, the total collected energy from these flexible distributed energy resources as well as the cost savings achieved by DSO in each month of 2016 are analyzed under each pair of these DSO policies. The payoff of transactive agents with different capacity sizes are computed. For each transaction trigger policy, the realized rate of permission arrivals are compared to the estimated ones.

To summarize, this paper aims to address the following valuation problems:

- *Value of the nonbinding transactive market for DSO, measured by the total collected energy [MWh]*
- *Value of the nonbinding transactive market for DSO, measured by the total cost saving [$]*
- *Value of the nonbinding transactive market for transactive agents, measured by the collected payoff [$]*

This paper is organized as follows. Section II presents the transactive energy market framework introduced in [12]. The control problems of DSO and transactive agents are discussed in Sections III and IV, respectively. Section V explains the data from NYISO. Section VI describes computational results of the DSO's proposed transaction trigger policy and agent selection policy. The paper is concluded in Section VII.

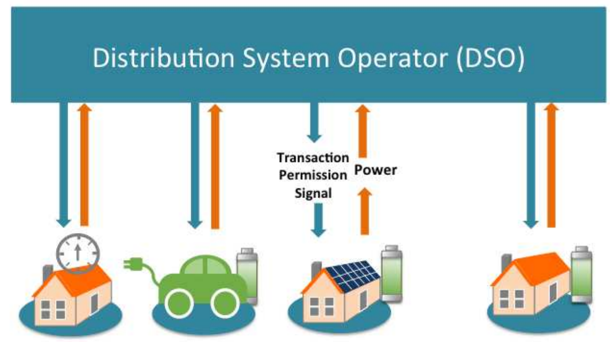


Fig. 1. Interactions between DSO and Transactive Agents with flexible capacities (e.g., Residential customers with storage, Prosumers, Electrical vehicles, or Residential customers with demand management).

II. A Nonbinding Transactive Energy Market

The novel nonbinding transactive energy market, proposed in [12], is adopted. The market enables transactions between distributed flexible energy resources, referred to as *transactive agents*, and a *distribution system operator (DSO)*.

In this framework, flexible capacity owners enroll in the market and express their willingness to receive transaction (discharge) permission signals from DSO. However, they are not required to make an advance commitment to provide power, should they receive such a transaction permission from DSO. Similarly, DSO does not commit to let them discharge at specified times and buy their discharged power. Figure 1 illustrates the interaction between DSO and distributed transactive agents with flexible energy resources.

The market operates during a time horizon $[0, T]$ of a day, e.g., [7am-11pm]. Should an agent, who received a transaction permission signal from DSO at time t, choose to discharge a units of electricity, he will be paid a contractual profit of $R_t(a)$. The payoff function is nonnegative, $R_t(0) = 0$, increasing in a, concave in a, and continuous in t everywhere. An example of the reward curve is

$$R(\theta_t, a) = \log(1 + \theta_t a) \tag{1}$$

for some time-varying payoff parameter θ_t, e.g., see Fig. 2.

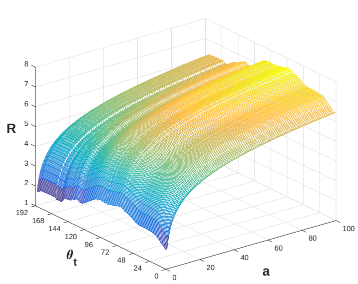


Fig. 2. Reward function $R(\theta_t, a)$ corresponding to the payoff parameters $\{\theta_t\}_t$ in July, depicted in Fig. 3 (b).

III. Distribution System Operator Control

Suppose there are N agents, indexed by $i = 1, \cdots, N$, who have enrolled in the transactive market. A DSO controller with two policies, *transaction trigger policy* and *agent selection policy*, are introduced.

The transaction trigger policy decides on whether to dispatch transaction permission signals at a time t. The agent selection policy decides on the subset of agents, $\mathcal{N}_t^* \subseteq \{1, 2, \cdots, N\}$, who are granted the transaction permissions at time t. Figure 3 depicts the DSO controller. Here,

$\tilde{p}_t$: real-time electricity price,

$\tilde{D}_t^\delta$: unforecasted load,

$a_t(k_{i,t})$: optimal policy of agent i with charge level k_i,

ς_t : threshold parameter in transaction trigger policy.

The unforecasted load $\tilde{D}_t^\delta$ is approximated by the deviation of the real-time load from the day-ahead demand.

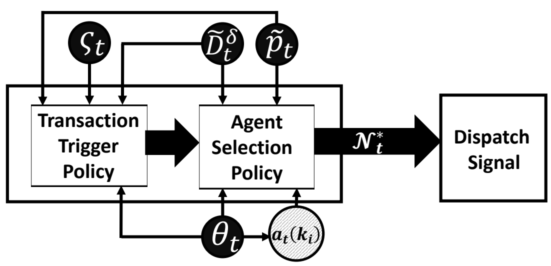


Fig. 3. Distribution System Operator Controller

This paper introduces three transaction trigger policies π_1, π_2, π_3 and three agent selection policies A, B, C defined on the state of the grid, including the electricity price and load. Table II summarizes these policies. Transaction trigger policies imply that DSO turns into the transactive market and issues discharge permissions when the forecasted demand is below the real-time demand ($\tilde{D}_t^\delta > 0$), or when the real-time price is higher than the payoff to be paid to the agent ($\tilde{p}_t \geq \theta_t$), or when the real-time electricity price (LMP) is higher than a threshold level ($\tilde{p}_t \geq \varsigma_t$).

TABLE II
Distribution System Operator Policies

Transaction Trigger Policy
$[\pi_1]$ $\tilde{D}_t^\delta > 0$
$[\pi_2]$ $\tilde{D}_t^\delta > 0$ and $\tilde{p}_t \geq \theta_t$
$[\pi_3]$ $\tilde{p}_t \geq \varsigma_t$, for some deterministic parameter ς_t

Agent Selection Policy
[A] $\mathcal{P}(\tilde{D}_t^\delta, \mathcal{N})$
[B] $\mathcal{P}(\tilde{D}_t^\delta, \mathcal{N}^+)$, where $\mathcal{N}^+ \subseteq \mathcal{N}$ is given by $\{i \in \mathcal{N} \text{ s.t. } \tilde{p}_t a_t(k_{i,t}) - R(\theta_t, a_t(k_{i,t})) > 0\}$.
[C] $\mathcal{P}(\tilde{D}_t^\delta, \mathcal{N})$, with the additional constraint $\sum_{i \in \mathcal{N}_t} (\tilde{p}_t a_t(k_{i,t}) - R(\theta_t, a_t(k_{i,t}))) > 0$.

Agent selection policies are defined by the optimization problem $\mathcal{P}\left(\tilde{D}_t^\delta, \mathcal{N}\right)$, given by

$$\mathcal{P}\left(\tilde{D}_t^\delta, \mathcal{N}\right): \quad \max_{\mathcal{N}_t \subseteq \mathcal{N}} \; f(\{a_t(k_{i,t})\}_{i \in \mathcal{N}_t}) \quad \text{s.t.} \sum_{i \in \mathcal{N}_t} a_t(k_{i,t}) \leq \tilde{D}_t^\delta. \tag{2}$$

Here, $\mathcal{N} \stackrel{\text{def}}{=} \{1, 2, \cdots, N\}$, and

$$\mathcal{N}^+ \stackrel{\text{def}}{=} \{i \in \mathcal{N} \text{ s.t. } \tilde{p}_t a_t(k_{i,t}) - R(\theta_t, a_t(k_{i,t})) > 0\}. \tag{3}$$

In this paper, $f(\{a_t(k_{i,t})\}_{i \in \mathcal{N}_t}) \stackrel{\text{def}}{=} \sum_{i \in \mathcal{N}_t} a_t(k_{i,t})$. Thus

$$\mathcal{N}_t^* = \arg \max_{\mathcal{N}_t \subseteq \mathcal{N}} \; \mathcal{P}\left(\tilde{D}_t^\delta, \mathcal{N}\right). \tag{4}$$

Problem (2) is expressed by an integer optimization problem:

$$\max_{c_1, \cdots, c_N \in \{0,1\}} \sum_{i=1}^N c_i a_t(k_{i,t}) \text{ s.t. } \sum_{i=1}^N c_i a_t(k_{i,t}) \leq \tilde{D}_t^\delta. \tag{5}$$

Thus, for policy [B], the constraints are included

$$c_i \left(\tilde{p}_t a_t(k_{i,t}) - R(\theta_t, a_t(k_{i,t}))\right) \geq 0, \quad i = 1, \cdots, N. \tag{6}$$

Policy [C] imposes the following constraint

$$\sum_{i=1}^N c_i \left(\tilde{p}_t a_t(k_{i,t}) - R(\theta_t, a_t(k_{i,t}))\right) \geq 0. \tag{7}$$

In the policy $[\pi_2]$, the condition $\tilde{p}_t \geq \theta_t$ implies that

$$\tilde{p}_t \geq \theta_t \geq \frac{\theta_t}{1 + \theta_t a} = \frac{dR(\theta_t, a)}{da},$$

which yields $p_t a - R(\theta_t, a)$ is an increasing function of a. Hence, when the transaction trigger policy $[\pi_2]$ is employed, the three agent selection policies result in the same $\mathcal{N}_t^*$.

Since the constraints $\tilde{p}_t a_t(k_{i,t}) - R(\theta_t, a_t(k_{i,t})) > 0$ for all i yield $\sum_{i=1}^N \tilde{p}_t a_t(k_{i,t}) - R(\theta_t, a_t(k_{i,t})) > 0$, the level of collected energy in policy $[C]$ is higher than the level of collected energy in policy [B].

The transaction trigger policy is contractual, i.e., both DSO and transactive agents have knowledge about which policy is applied to transaction trigger permissions. Therefore, while agents do not have information about the exact time when they can discharge, they can compute the arrival rate of transaction permissions given the transaction trigger policy in the contract.

IV. Transactive Agent Control

From a transactive agent's point of view, transaction permissions arrive at random following a Poisson process with intensity λ. When a discharge permission signal is dispatched to an agent at time $t \in [0, T)$, he can choose to discharge a at the payoff $R(\theta_t, a)$.

An optimal policy of a risk-neutral transactive agent is determined by maximizing total expected payoff over $[0, T]$. This results in the following dynamic optimization problem

$$\max_{x^\pi \in \mathcal{X}_0} \mathbb{E}\left[\sum_{\ell=1}^{Z_{T-}} R\left(\theta_{\tau_{\ell,0}}, x^\pi_{\tau_{\ell-1,0}} - x^\pi_{\tau_{\ell,0}}\right) \;\middle|\; x_0^\pi = k\right], \tag{8}$$

with the optimal objective value $V_0(k)$. The expectation in (8) is over the Poisson process $\{Z_s\}_{s\geq 0}$. Here, $\mathcal{X}_0$ is the set of all nonnegative real-valued, right-continuous with left limits, decreasing process $x^\pi = \{x_t^\pi\}_{t\in[0,T]}$ adapted to the filtration $\{\mathcal{F}_t\}_{t>0}$. The process x^π represents the charge level under the agent policy π. The random variable Z_{T-} is the number of transaction permission arrivals $\{Z_s\}_{s\geq 0}$ over the time interval $[0,T)$. Assumption $R(\theta_t, 0) = 0$ yields $V_0(0) = 0$.

The optimal value functions $V_t(k)$ of this Markov Decision Process (MDP) satisfy the dynamic programming equation:

$$V_t(k) = \mathbb{E}\left[\max_{a\in\mathcal{A}_k}\left\{R(\theta_{\tau_{1,t}}, a) + V_{\tau_{1,t}}(k-a)\right\}\cdot 1_{\tau_{1,t}<T}\right], \quad (9)$$

where the expectation is over the time $\tau_{1,t}$ of the next transaction permission.

Various properties for the value function and optimal policy $a_t(k)$ are established in [12], and an approach to compute the optimal value function is proposed. As the agent receives a transaction permission at time t when the available capacity is k, the optimal discharge amount, $a_t(k)$, is given by

$$a_t(k) = \arg\max_{a\in\mathcal{A}_k}\ \left\{R(\theta_t, a) + V_t(k-a)\right\}. \quad (10)$$

V. Data

The data from New York Independent System Operator (NYISO), Zone K-Long Island (LONGIL), from 1-Jan-2016 to 31-Dec-2016 is used. Real-Time Locational Based Marginal Price (LBMP) data is used to approximate the time-varying payoff parameter $\{\theta_t\}_t$. Fig. 4(a) illustrates the daily real-time electricity price averaged over a month, for January and July (the months with highest and lowest temperature in Long Island). Smoothing filters such as moving average with some span coefficient can be used to smooth out the curves, which cast as $\{\theta_t\}_t$, see Fig. 4(b) for moving average with span 24.

The real-time load and day-ahead load data sets are employed to approximate the unforecasted demand $\tilde{D}_t^\delta$, i.e., $\tilde{D}_t^\delta = \max\{0, \tilde{D}_t - \mathbb{E}[\tilde{D}_t]\}$, where $\mathbb{E}[\tilde{D}_t]$ is approximated by the day-ahead hourly demand. The mean of $\tilde{D}_t^\delta$ varies from 30.56 and 41.61 in Jan and Mar, respectively, to 97.00 and 98.37 in Jul. and Aug in 2016.

Figure 4(c) illustrates $\tilde{D}_t^\delta$ for one day 7-Jan-2017. Transaction trigger policies for this day are depicted in Figures 5(a)-5(c). Figure 7 shows arrival rates per hour for two days, 16-Jan-2016 and 16-Jul-2016 from the policy $[\pi_3]$ are illustrated in .

For each transaction trigger policy, the corresponding hourly transaction permission arrival rate averaged over all days of one month are computed in Table III.

VI. Simulation Results

The following criteria are used to assess the nonbinding transactive energy market:

- Collected Energy by DSO : $E_t = \sum_{i\in\mathcal{N}_t^*} a_t(k_{i,t})$. (11)
- Cost Saving for DSO : $J_t = p_t E_t - \sum_{i\in\mathcal{N}_t^*} R(\theta_t, a_t(k_{i,t}))$. (12)
- Payoff of the i^{th} agent : $\int_{t\in[0,T]} R(\theta_t, a_i)\mathbf{1}_{i\in\mathcal{N}_t^*}dt$. (13)

TABLE III
PERMISSION INTENSITY PER TRANSACTION TRIGGER POLICY

	Jan	Feb	Mar	Apr	May	Jun
λ^{π_1}	5.25	7.02	5.28	3.48	4.46	5.17
λ^{π_2}	2.04	2.00	1.99	1.56	1.92	2.13
λ^{π_3}	4.29	3.31	0.92	1.96	1.36	2.44
	Jul	Aug	Sep	Oct	Nov	Dec
λ^{π_1}	5.27	7.06	4.35	6.94	6.85	6.53
λ^{π_2}	2.59	2.81	1.63	2.07	2.00	2.82
λ^{π_3}	5.44	6.68	3.11	0.94	1.99	8.04

TABLE IV
ANNUAL PAYOFF [$] OF AGENTS FOR EACH DSO POLICY.

Transaction Trigger Policy	Agent Selection Policy	Agent 1	Agent 2	Agent 3	Agent 4	Agent 5
π_1	[A]	7,302	10,111	12,693	15,025	17,212
π_1	[B]	4,726	6,873	8,976	10,962	12,872
π_1	[C]	5,251	7,332	9,282	11,115	12,869
π_2	[A]	4,777	6,392	7,755	8,929	9,991
π_3	[A]	4,322	5,830	7,154	8,305	9,374
π_3	[B]	3,691	5,075	6,321	7,431	8,499
π_3	[C]	3,839	5,194	6,406	7,483	8,500

We consider a market with $N = 5$ transactive agents, with capacities $K_1^{\text{cap}} = 10$, $K_2^{\text{cap}} = 15$, $K_3^{\text{cap}} = 20$, $K_4^{\text{cap}} = 25$, and $K_5^{\text{cap}} = 30$. This study assumes that the transactive agents compute their controls $a_t(k_i)$ corresponding to λ^{π_i} in Table III per month. The initial charge level per day is set to $k_{i,0} = K_i^{\text{cap}}$.

Table IV summarizes the payoff of the agents for the entire 2016 under each DSO policy. The cost savings of DSO $\sum_t J_t$ and total energy collected $\sum_t E_t$ are reported in Tables V and VI. Detailed payoffs of the agents per month are depicted in Fig. 8 for policy π_2.

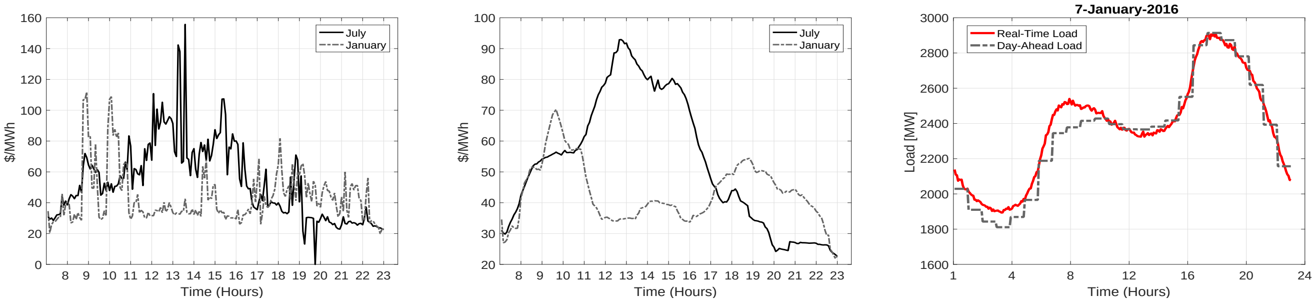
Figure 6 depicts the averaged realized arrival rates by the agents and λ^{π_i}s computed from the transaction trigger policies in Table III. Among the three policies, the transaction trigger policy π_2 offers an arrival rate closer to the nominal one.

VII. Discussion and Conclusions

The following observations are made from the simulation results. From Table IV, the amounts received by the agents is generally higher with π_1. Indeed the arrival rates under π_1 are higher, see Table III. Interestingly, the amounts grow less than proportionally with the agent capacities, indicating the system favors agents with a relative smaller capacity. This conclusion holds for any combination of DSO policies.

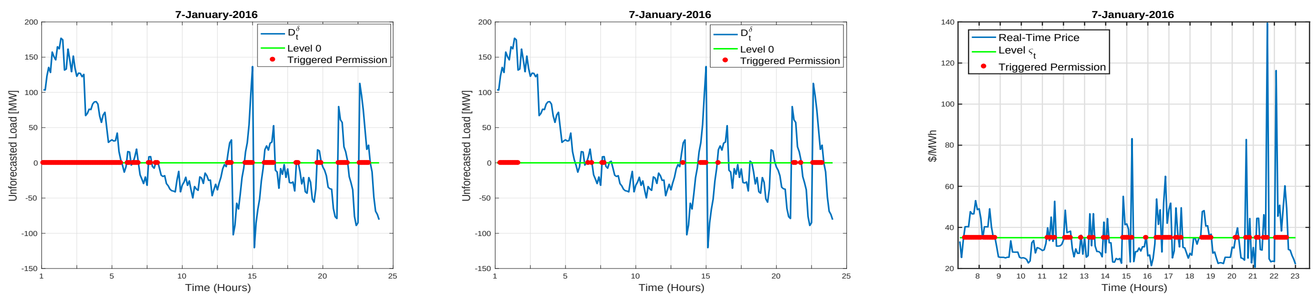
The policy π_2 is the most attractive for the DSO, given the total cost savings J, see Tables VI and V. From Fig.6, we observe that π_2 is the policy for which the realized arrival rate is closest to the nominal rate. The policy π_2 remains attractive in terms of total payoff received by each agent, ranging from about 4000 to 10000 depending on the capacity. Compared to π_3, the amounts per month are also more stable with π_2.

We conclude that the among the set of policies investigated in this paper, the two policies π_2 and $\pi_1[A]$ have more favorable



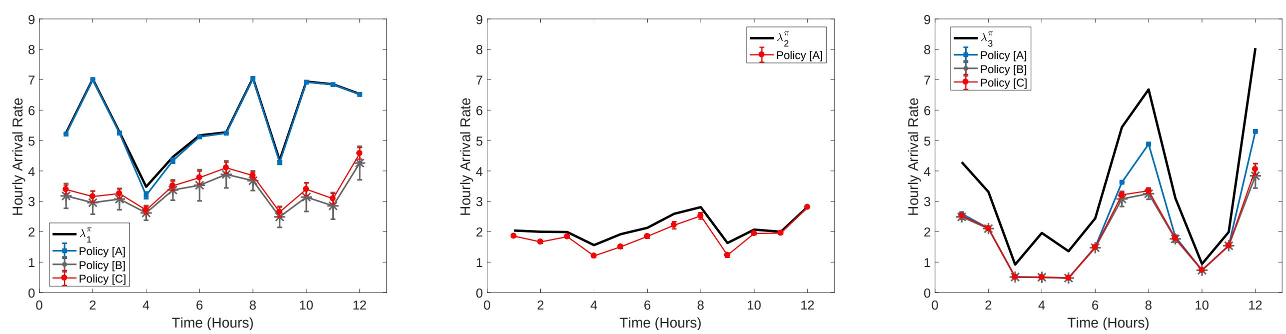
(a) Average Real-Time Prices (b) θ_t: Smoothed Average Real-Time Prices (c) Real-Time Load versus Forecasted Load

Fig. 4. Real-time prices to compute payoff parameters $\{\theta_t\}_t$. Real-time load versus Day-ahead load ($\tilde{D}_t^{\delta}$).



(a) Transaction Trigger Policy π_1 (b) Transaction Trigger Policy π_2 (c) Transaction Trigger Policy π_3

Fig. 5. Transaction trigger policies for one day (7-Jan-2016). In [π_3], the threshold parameter is set to ς_t=35 [$/MWh] for all t.



(a) Transaction Trigger Policy π_1 (b) Transaction Trigger Policy π_2 (c) Transaction Trigger Policy π_3

Fig. 6. Hourly Realized Arrival Rate versus Nominal Arrival Rate for various DSO Policies.

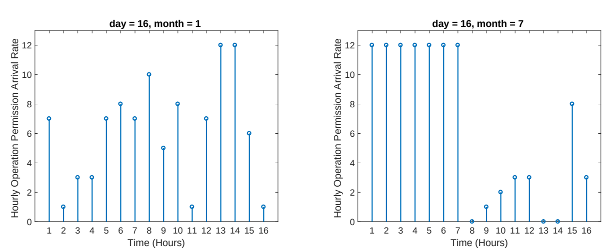


Fig. 7. Operation Permission Arrival Rates per Hour for 16-Jan-2016 and 16-Jul-2016, for transaction trigger policy [π_3] with ς_t= 35 [$/MWh].

properties. Both are able to offer a realized permission arrival rate close to the expected arrival rates. Policy π_2 brings the DSO the highest cost saving while policy $\pi_1[A]$ brings the agents the most total and stable payoff.

ACKNOWLEDGMENT

This material is based upon work supported by the National Science Foundation under Grants No. 1610302 and 1610825. Authors thank Amir H. Hajimiragha for his comments and feedback on this work.

TABLE V

TOTAL COLLECTED ENERGY PER MONTH (E), MAXIMUM COLLECTED ENERGY PER TRANSACTION ($\Delta^{\max}$), TOTAL COST SAVING FOR DSO (J)

Month	**Agent Selection Policy [A]**			**Agent Selection Policy [B]**			**Agent Selection Policy [C]**		
	E [MWh]	$\Delta^{\max}$ [MWh]	J [\$]	E [MWh]	$\Delta^{\max}$ [MWh]	J [\$]	E [MWh]	$\Delta^{\max}$ [MWh]	J [\$]
Jan	2302.70	8.20	4602	1990.92	9.77	6950	2024.02	9.72	6751
July	1799.50	5.16	4932	1682.80	6.34	6091	1700.23	5.83	5933
12m Total	26,658.30		35,525	22,098.16		50,735	22,463.91		49,706

(a) Transaction Trigger Policy $[\pi_1]$

Month	**Agent Selection Policy [A]**			**Agent Selection Policy [B]**			**Agent Selection Policy [C]**		
	E [MWh]	$\Delta^{\max}$ [MWh]	J [\$]	E [MWh]	$\Delta^{\max}$ [MWh]	J [\$]	E [MWh]	$\Delta^{\max}$ [MWh]	J [\$]
Jan	1580.73	13.59	8800	1575.41	13.59	8881	1578.44	13.59	8854
Jul	1280.97	5.62	5359	1175.94	5.86	6000	1199.20	5.80	5903
12m Total	15,299.58		78,164	14,620.56		80,786	14,700.70		80,572

(b) Transaction Trigger Policy $[\pi_3]$

TABLE VI

TOTAL COLLECTED ENERGY PER MONTH (E), MAXIMUM COLLECTED ENERGY PER TRANSACTION ($\Delta^{\max}$), TOTAL COST SAVING FOR DSO (J)

Month	Agent Selection Policy [A]		
	E [MWh]	$\Delta^{\max}$ [MWh]	J [\$]
Jan	1869.56	29.11	15323
Feb	1524.88	20.89	10105
Mar	2615.56	41.16	6061
Apr	2735.34	69.61	4967
May	2161.06	32.64	4076
June	2314.17	39.81	11331
July	1549.17	9.34	10256
Aug	1609.56	13.12	17680
Sept	1116.12	25.45	6747
Oct	1818.20	16.05	4737
Nov	1616.77	5.45	5711
Dec	1757.19	4.69	7727
Total	22,687.59		104,722

Transaction Trigger Policy $[\pi_2]$

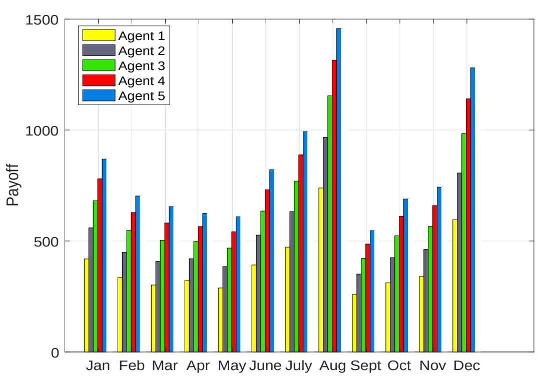


Fig. 8. Agents' Payoffs per Month for Transaction Trigger Policy $[\pi_2]$.

REFERENCES

[1] M. I. Olken, "Transactive energy: Everyone gets into the act," *IEEE Power & Energy Magazine*, vol. 14, no. 3, pp. 4–16, 2016.

[2] E. Cazalet, P. D. Martini, J. Price, E. Woychik, and J. Caldwel, "Transactive energy models," *NIST Transactive Energy Challenge: Business and Regulatory Models Working Group*, pp. 1–44, 2016.

[3] F. Rahimi and F. Albuyeh, "Applying lessons learned from transmission open access to distribution and grid-edge transactive energy systems," *Innovative Smart Grid Technologies Conference (ISGT), IEEE Power & Energy Society*, pp. 1–5, 2016.

[4] Y. Xiao, Q. Su, F. Bresler, R. Carroll, J. Schmitt, and M. Olaleye, "Performance-based regulation model in PJM wholesale markets," in *2014 IEEE PES General Meeting, Conference Exposition*, July 2014, pp. 1–5.

[5] "Gridwise transactive energy framework version 1.0," GridWise Architecture Council, Tech. Rep. PNNL-22946, january 2015.

[6] DOE Report, "The importance of flexible electricity supply," *Energy Efficiency and Renewable Energy Report*, vol. DOE/GO-102011-3201, pp. 1–4, 2011.

[7] Energy Research Knowledge Centre Report, "Research challenges to increase the flexibility of power systems," *European Union*, pp. 1–38, 2014.

[8] D. Bhatnagar, A. Currier, J. Hernandez, O. Ma, and B. Kirby, "Market and policy barriers to energy storage deployment, a study for the energy storage systems program," *Sandia National Laboratories Report*, vol. SAND2013-7606, pp. 1–58, 2013.

[9] J. Straubel, "Energy storage, EV's and the grid," *EIA Conference, Washington D.C.*, pp. 1–29, 2015.

[10] Quadrennial Energy Review, "Energy transmission, storage, and distribution infrastructure," *Quadrennial Energy Review*, pp. 1–348, 2015.

[11] S. Barrager and E. Cazalet, *Transactive Energy: A Sustainable Business and Regulatory Model for Electricity*, 1st ed. Baker Street Publishing, 2014.

[12] S. Moazeni and B. Defourny, "An energy storage deployment program under random discharge permissions," Lehigh University, Tech. Rep. 15T-012, 2015.