A Software Platform for Developing Transactive Energy Markets

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***Abstract*—Recent trends and technological breakthroughs are changing the way electric power systems are structured and operated. A central role in this new system will belong to the prosumer (producer and consumer in one entity) who will actively participate in the system and make choices of how electricity is generated, used and exchanged. At the same time, this transactional energy system promises benefit utilities by providing new tools that will help increase system efficiency. This paper introduces the Transactive Renewable Energy Exchange (TREX), a software tool for co-design of market and artificial intelligence-based participants. TREX proved to be a valuable simulation environment that allowed the economy of MicroTE be analyzed emperically using an Agent-based computational economics (ACE) approach. Results showed that grid stability improved, and financial improvements were achieved. Further improvements are expected as the AI portion of this research advances.**

I. Shifting to a Renewable-Centric Grid

Renewables will be an important step in preserving the environment. The challenge with shifting to a renewable-centric grid is the intertwining of market, operations, and participation. Some or all of these components must be changed to enable better utilization of the renewable resources, while ensuring that changes bringing benefit to one area do not negatively affect others.

To determine the right changes, a holistic and systematic approach is required. Real life testing with pilot projects is expensive and risky. We propose a software solution to test designs in simulation.

II. Background

A. Traditional Electricity Market

The current electricity market (Figure 1), which will be referred to as the "traditional market", is hierarchical. It follows a tiered topology where power flows one-way from the generators to the consumers, and money flows in the reverse direction of power. The traditional market was designed based on the assumption that loads can be predicted to a near-perfect degree of accuracy, and therefore generation can be planned and scheduled.

The traditional market works well and efficiently while the assumptions are true. However, increasing penetration of renewable energy (RE) and distributed energy resource (DER) will break these assumptions. First, generators no longer have complete control of generation dispatch, as RE generation (such as solar and wind) must be dispatched immediately. Second, due to infrastructure and regulatory constraints, utility companies do not have information on most residential REs and DERs, causing the loads to be less predictable. In areas with high levels of RE penetration, it is becoming increasingly difficult to schedule generation to match load, leading to symptoms such as the duck curve, localized voltage violations, and volatile electricity prices.

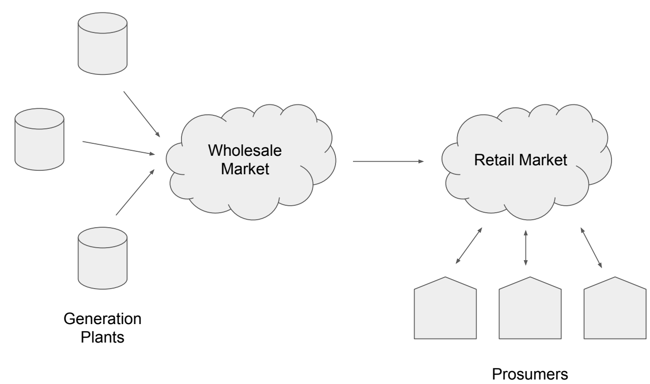

Fig. 1. Traditional Electricity Market

B. Transactive Energy Market

The concept of Transactive Energy (TE) market (Figure 2) was introduced as a framework to address the shortcomings of the traditional market. It was proposed as an information management and flow exchange framework which supersedes the traditional grid with a network of energy nodes [1], [2]. In a TE environment, every energy node is allowed to exchange information and energy with any other node on the network. This information enables more fine-grained control, and therefore higher efficiency and stability of the grid.

Since TE is a general concept, specific implementation details are left to the designers. The proposed approach, dubbed TREX, aims to implement TE using a decentralized, economics-based approach to give prosumers more ownership and control of their DERs, while still bringing benefits to the grid as a whole.

C. Agent-based Computational Economics

Real-world economies exhibit five essential properties [3]:

1) The world consists of heterogeneous interacting participants;

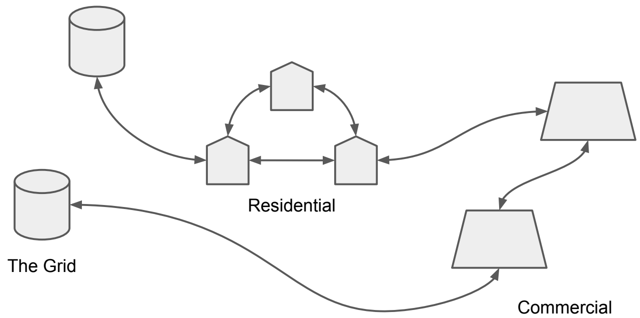

Fig. 2. Transactive Energy Market

2) The world dynamics are driven by successive interactions of participants;
3) Participants decisions take into account previous actions and potential future actions by other participants;
4) All participants are locally constructive;
5) Actions taken by participants at any given time affect future local states.

These properties imply that real-world economies can be modeled as locally-constructive sequential games. Agent-based Computational Economics (ACE) [ref ace] is an approach that models economic processes as open-ended dynamic systems of interacting agents. ACE delivers an analysis of agent-agent interactions without any modeler-imposed rationalities conditional on a pre-constructed economic model. Because of this impartiality, ACE is likely one of the most accurate ways to computationally study market design.

D. Reinforcement Learning

Reinforcement learning (RL) is a type of machine learning (ML) in which an entity, referred to as an agent, learns through trial-and-error interaction with its environment [4]. An agent performs actions and is provided feedback on the *impact* of these actions through a scalar value known as reward r_t. The goal is to maximize the sum of future rewards known collectively as the return $G_t = \sum_{t=0}^{\infty} r_t$. In addition to rewards, the agent also collects information about the environment through observations o_t. Through rewards and observations, agents learn policy $\pi(o_t)$ that guides their actions. To formulate this policy, agents keep tabs on the value of states, $V_t(s) = \mathbf{E}[G_t|S_t = s]$, or quality of state action pairs, $Q_t(s,a) = \mathbf{E}[G_t|S_t = s, A_t = a]$.

Since RL agents learn through trial and error, they extract information about their environment through the feedback on their actions. Since agents seek to maximize return, they must have a mechanism to gain information about their environment; this is known as exploration. The balance between exploring the environment and exploiting information already known to the agent is of pivotal significance across RL learning algorithms. A popular way to create an exploratory drive is to inject a random action selection with a certain probability ϵ, this is known as ϵ-*greedy* exploration.

E. Double Auctions

A double auction is a bilateral trading process in which the buyers and the sellers simultaneously submit their bids (b) and offers (s) to an auctioneer. The auctioneer then chooses some settlement price, p, to clear the market. All sellers who offered less than p sell at p, and buyers who bid more than p buy at p. Bid and offer prices at p are inclusive. Double auctions represent a simple method to enable bilateral trading. They have also been used as tools to study the determination of prices in ordinary markets.

III. TREX Simulation Framework

A. Market-centric Design Approach

The purpose of a market is to enable the efficient allocation of scarce resources [5]. For a producer, this means choice in producing the same goods or services with alternative resources for the most competitive prices (i.e. different types of generation). For a consumer, this means that a cheaper option is always available from several functionally identical products (i.e. buying electricity from the grid, or from a neighbouring prosumer).

Competitive markets serve another purpose [5]: to enable distributed coordination amongst participants. Price allows individual producers of the same product to decide whether to adjust supply, without needing to directly communicate with each other. Likewise, consumers independently decide whether the product is worth buying at the price offered, and collectively change demand. Numerous independent decisions and minor adjustments are made over time, until the market reaches equilibrium, when the market is operating at optimal efficiency. It is important to note that the price is a reflection of supply and demand. Approaches that attempt to use price to control demand misinterpret the role of prices, and will only make the consumers seek out alternative sources of supply to satisfy their demand [5].

As RE and DER penetration increases, the electricity market will favor a free-market configuration, where collective coordination is achieved through competition. We hypothesize that with proper market design and proper agents, the grid can improve both economic efficiency and stability in comparison to the status quo.

B. Transactive Renewable Energy Exchange (TREX)

In-depth, theoretical analysis have been conducted on using TE as a coordination mechanism for DERs [6], [7]. However, tools that allow for detailed, empirical studies of TE, especially at the individual household level, are still rare [8]. The few simulation tools that are available use a model-based approaches that generally suffer from modeler imposed rationalities, and may not be as truthful as ACE-based simulations.

Engineering markets with ACE is simple in concept, but difficult in execution. A major part of the difficulty is requirement of heterogeneously interacting agents. In a human-centric approach, behaviour models of all human participants in the intended area of deployment must be accurately captured in order to properly evaluate the market. This approach is difficult as human behaviour is affected by multiple outside factors.

The next logical approach is to fully automate energy trading and management. A popular way is with rule-based expert systems, which are often designed by individual prosumers based on their own experience. Expert systems are generally designed for specific cases, and cannot easily adapt to a dynamic environment such as a TE market without a large number of rules. Therefore, relying on individual prosumers who have limited time and experience is inadequate.

Fortunately, with recent developments in ML, it is possible to design adaptable, AI agents. However, as agents require a properly designed environment that fosters learning, they need to be co-developed alongside markets. This is challenging, but also necessary, as AI alone will not be able to address all the technical problems of increased DER. A holistic system that trains AI agents to operate in a market designed for ML will allow better utilization, and should result in both financial advantage and increased grid stability.

C. System Architecture

The TREX architecture (Figure 3) is modular, scalable, and designed to take advantage of modern ML frameworks.

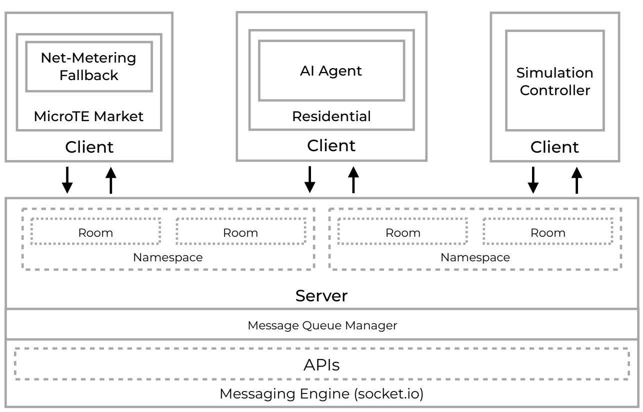

Fig. 3. Current Architecture of the TREX Simulator

D. Market Design

Because markets designed under TREX are implemented in software, the set of mechanisms that define the market must be explicit and specific, and leave no room for misunderstanding. This is an advantage over traditional market definitions, where the language is open for legal interpretation.

To design a market under TREX, the designer must be familiar with the types of agents that will be used to manage and trade energy. The market should be tailored to the agents' learning algorithms, so that the provided feedback is most useful for learning.

E. Micro-Transactive Energy Market (MicroTE)

The MicroTE (Figure 4) is the primary market designed and studied under TREX. It is a bottom-up approach designed to encourage better utilization of local DERs, so that the energy flow within each MicroTE can be more balanced, thus making the grid more stable. Due to the hyper-local and distributed nature of MicroTEs, nodal pricing is built-in. This automatically creates opportunities for physical energy arbitrage through mobile DERs, and may result in further improvement of grid stability.

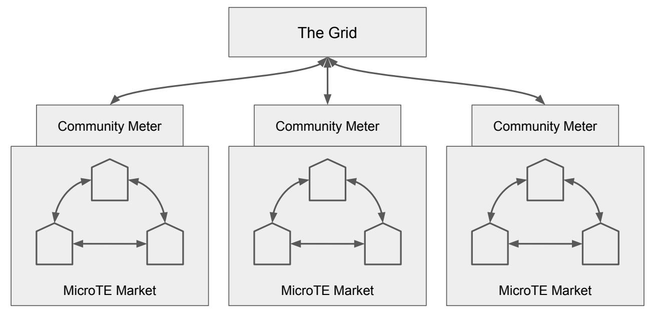

Fig. 4. MicroTE Markets connected to the grid

The settlement method in MicroTE takes inspirations from double-auctions and forwards (a forward is a non-standardized contract to buy or sell an asset at a specified time in the future and at a predetermined price, between parties unknown to each other). Other settlement strategies will be extensively studied later on, as they heavily affect characteristics of the market [9].

The following set of rules describe the basic operations of a MicroTE.

1) The grid is always available. Energy transacted with the grid is done through net-metering.
2) Any energy effectively bought from the grid is priced at 144.9 cents/kWh. Any energy effectively sold to the grid is priced at 69 cents/kWh. This is in line with retail net billing prices in Alberta as of November 2019.
3) Auction rounds last for a maximum of 1 minute.
4) The delivery period is 15 minutes from the current auction round, and it lasts for the duration of an auction round. During each auction round, participants may:
   a) Bid for energy that other participants may produce during the delivery period.
   b) Offer energy that they are predicting to produce during the delivery period.
5) Bids/offers are matched and settled pairwise. Bids are sorted from the highest to the lowest price, and offers are sorted in reverse. Settlement price is the average of bid and offer prices if bid price is greater than or equal to offer price.
6) Bids/offers can be partially settled.
7) Energy quantity must be an integer multiple of 1 Wh. Real-time meter readings are used to validate physical energy transactions.
8) During the delivery period, if a seller generates less than settled, then the seller must financially compensate the buyer for the shortage at net metering prices.
9) During the delivery period, if a buyer settled for more than used, the buyer must still pay for the extra energy

at settlement price. The seller may not be compensated for the extra generation in any other way.

Individual transactions in TREX are recorded in a ledger at the time of delivery. Each transaction contains eleven strategically selected fields to provide the minimum amount of information necessary for billing and analysis. This also minimizes the hardware requirements.

1) Settlement ID
2) Settlement quantity
3) Seller ID
4) Buyer ID
5) Energy source
6) Settlement price
7) Seller fee
8) Buyer fee
9) Time of creation
10) Time of settlement
11) Time of delivery

Auctions were chosen over a peer-to-peer design to maximize data efficiency and scalability, as the overhead for peer discovery and negotiations grows exponentially with the number of participants, whereas the overhead for auction is constant. Auctions also obscure some participant information and make sniping from malicious actors more difficult. The reasons for using integer multiples of 1 Wh as the quantity are three-fold: first, integers are more data efficient than floating point numbers; second, as most smart meters are capable of producing pulse-watts (1 pulse for 1 Wh of energy accumulated), gathering energy information in this format is acceptable; finally, in our experiments, the aggregated quantization error over one year for a typical home is less than 0.05%, which more than satisfies the class 0.1% standards [10], [11].

F. Participants

In the ACE model, every action by every participant have consequences. In the electricity market, every action affects both power and market in some way. Market designs that do not consider effects on power are destined to suffer problems that have already been experienced in certain parts of the world [12], [13].

In any form of market, the participant has two interfacing functions:

- Intention to buy
- Intention to sell

These two actions can be specified as functions of four variables: asset, quantity, price, and time of delivery. The role of the participant is to learn the appropriate action variables that lead to maximum financial advantage. Since MicroTE is designed to financially incentivizes local energy exchanges, then the agents will learn that it is more financially advantageous to buy and sell energy to/from neighbours. Doing so should result in distributed coordination of energy balance, thus improving voltage stability.

Participants in MicroTE market are required to perform tasks with the following characteristics:

- Imperfect information
- Long term planning
- Real time decision making
- Large action space

Being able to operate with imperfect information is particularly important. Unlike games such as Go and Chess, where agents have perfect information of the environment and the actions of the other agent, the market obscures the actions of the other agents, making the world only partially observable. Furthermore, perfect information cannot be guaranteed due to other factors, such as networking errors.

Recent developments in AI, shown through projects such as OpenAI, AlphaStar, and AlphaGo [14]–[16], suggest that AI can perform complex tasks in a multi-agent settings with these characteristics at close-to-superhuman levels. As MA RL is nascent, and environments for studying RL in MA settings are scarce, TREX and MicroTE may be useful as an environment to push MA RL forward, while simultaneously producing results that are useful in real world applications.

IV. Experimental Design

The primary goal of this experiment is to show TREX proof-of-concept. We do this by answering two questions:

1) Can RL agents can learn to operate within MicroTE?
2) Can the combination of MicroTE and RL agents can achieve financial advantage and increased grid stability?

Because this experiment heavily relies on AI research, the agents are simple and the training methods are work in progress. However, if there is evidence of these two answers even with simple agents, then the results can be expected to get better as algorithms and training methods mature.

The RL agents used in the experiment use a tile-coder [4], [17] as state approximator and learn to maximize their average reward via 1-step Q-learning [4]. Q-learning is a RL algorithm for control, learning the target maximizing the quality Q based on an exploratory ϵ-greedy policy in an online fashion [4]. The agents are trained with an adapted version of competitive self-play [18].

Participant load and generation profiles are from real data from net-zero homes in Seattle from 2015 to 2019. A 7 kWh battery model is added to each participant for use via greedy control. Agent actions are limited to one bid and one offer in the solar energy pool per auction round. A net-metering equivalent simulation is run alongside the MicroTE simulation as a baseline for comparison. Power flow was analyzed using the benchmark community sub-circuit [19] with OpenDSS [20].

V. Results and discussion

The primary goal of the experiment was to find out whether RL agents can learn to operate within MicroTE, and whether the combination of MicroTE and RL agents can achieve both financial advantage and increased grid stability. Figure 5 clearly shows tighter node voltage distributions, which suggests increased grid stability.

Figure 6 shows the financial advantage of the agents compared to the baseline scenario. Two observations are immediately obvious: First, the grid is losing money over time, which suggests that more locally generated energy are being utilized

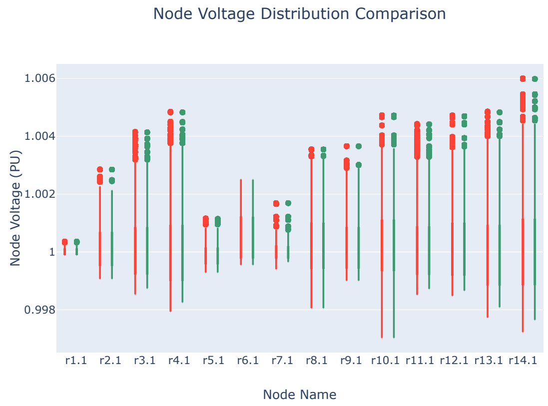

Fig. 5. Node voltage comparison on the test circuit between baseline (red/left) and MicroTE (green/right).

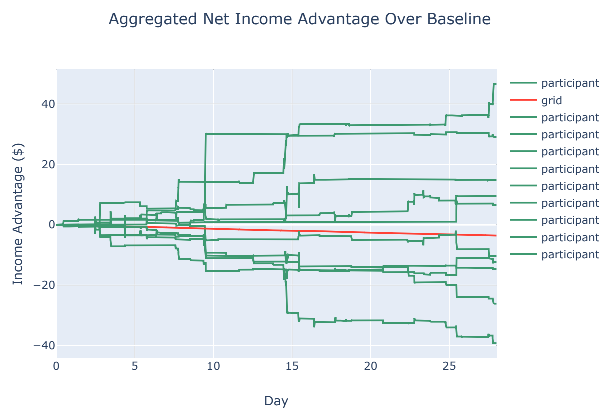

Fig. 6. Relative Financial Advantage over Baseline.

at the right time. Second, not all participants are financially better than the baseline. This suggests that the agents and/or the training pipeline still have room to improve. It is somewhat surprising and encouraging to see improved power flow even with sub-optimal agents. We should expect vastly better results in the future as the AI portion of this research advances.

VI. Conclusions

The shift to renewables has created new opportunities and new problems. This contribution introduces TREX as a simulation framework for co-designing of electricity market and AI-based market participants. The MicroTE market and RL agents were implemented and simulated using an ACE approach. TREX proved to be a valuable simulation environment that allowed the economy of MicroTE to be analyzed emperically. Results showed that financial improvements were partially improved, perhaps due to sub-optimal agent design. Even then,node voltages improved. Further improvements to both are expected as the AI portion of this research advances.

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References

[1] B. Li, C. Wan, K. Yuan, and Y. Song, "Demand response for integrating distributed energy resources in transactive energy system," *Energy Procedia*, vol. 158, pp. 6645 – 6651, 2019. Innovative Solutions for Energy Transitions.

[2] P. Siano, G. De Marco, A. Roln, and V. Loia, "A survey and evaluation of the potentials of distributed ledger technology for peer-to-peer transactive energy exchanges in local energy markets," *IEEE Systems Journal*, vol. 13, pp. 3454–3466, Sep. 2019.

[3] L. Tesfatsion, "Agent-based computational economics (tesfatsion)." http://www2.econ.iastate.edu/tesfatsi/ace.htm, 2019.

[4] A. Barto and R. Sutton, *Reinforcment Learning, an Introduction*. MIT Press, 2 ed., 2018.

[5] T. Sowell, *Basic Economics: A Citizen's Guide to the Economy*. Basic Books, 2003.

[6] S. Li, J. Lian, A. J. Conejo, and W. Zhang, "Transactive energy system: Market-based coordination of distributed energy resources.," 2019.

[7] M. S. Nazir and I. A. Hiskens, "A dynamical systems approach to modeling and analysis of transactive energy coordination," *IEEE Transactions on Power Systems*, vol. 34, pp. 4060–4070, Sep. 2019.

[8] Q. Huang, T. E. McDermott, Y. Tang, A. Makhmalbaf, D. J. Hammerstrom, A. R. Fisher, L. D. Marinovici, and T. Hardy, "Simulation-based valuation of transactive energy systems," *IEEE Transactions on Power Systems*, vol. 34, pp. 4138–4147, Sep. 2019.

[9] M. Babaioff and N. Nisan, "Concurrent auctions across the supply chain," *Journal of Artificial Intelligence Research*, vol. 21, p. 595629, May 2004.

[10] "Iec 62053 electricity meter specification."

[11] "Gb/t 17883-1999 electricity meter specification."

[12] W. Hogan, "Electricity market structure and infrastructure," 11 2019.

[13] C. Lo Prete, W. Hogan, B. Liu, and J. Wang, "Cross-product manipulation in electricity markets, microstructure models and asymmetric information," *The Energy Journal*, vol. 40, 09 2019.

[14] OpenAI, "Openai five." https://blog.openai.com/openai-five/, 2018.

[15] O. Vinyals, I. Babuschkin, J. Chung, M. Mathieu, M. Jaderberg, W. Czarnecki, A. Dudzik, A. Huang, P. Georgiev, R. Powell, T. Ewalds, D. Horgan, M. Kroiss, I. Danihelka, J. Agapiou, J. Oh, V. Dalibard, D. Choi, L. Sifre, Y. Sulsky, S. Vezhnevets, J. Molloy, T. Cai, D. Budden, T. Paine, C. Gulcehre, Z. Wang, T. Pfaff, T. Pohlen, D. Yogatama, J. Cohen, K. McKinney, O. Smith, T. Schaul, T. Lillicrap, C. Apps, K. Kavukcuoglu, D. Hassabis, and D. Silver, "AlphaStar: Mastering the Real-Time Strategy Game StarCraft II." https://deepmind.com/blog/alphastar-mastering-real-time-strategy-game-starcraft-ii/, 2019.

[16] D. Silver, A. Huang, C. J. Maddison, A. Guez, L. Sifre, G. van den Driessche, J. Schrittwieser, I. Antonoglou, V. Panneershelvam, M. Lanctot, S. Dieleman, D. Grewe, J. Nham, N. Kalchbrenner, I. Sutskever, T. Lillicrap, M. Leach, K. Kavukcuoglu, T. Graepel, and D. Hassabis, "Mastering the game of go with deep neural networks and tree search," *Nature*, vol. 529, no. 7587, pp. 484–489, 2016.

[17] Richard S. Sutton, "Tile coding software – reference manual, version 3 beta."

[18] T. Bansal, J. Pachocki, S. Sidor, I. Sutskever, and I. Mordatch, "Emergent complexity via multi-agent competition," 10 2017.

[19] K. Strunz, E. Abbasi, R. Fletcher, N. Hatziargyriou, R. Iravani, and G. Joos, *TF C6.04.02 : TB 575 – Benchmark Systems for Network Integration of Renewable and Distributed Energy Resources*. 04 2014.

[20] EPRI, "Electric power research institute, inc." https://smartgrid.epri.com/Index.aspx, 2019.