T-REX: A Software Platform for Developing Transactive Energy Markets

Shida Zhang[1], Mustafa Gül[2], Petr Musilek[13], *Senior Member, IEEE*
[1]Electrical and Computer Engineering, University of Alberta, Edmonton AB, Canada,
[2]Civil and Environmental Engineering, University of Alberta, Edmonton AB, Canada,
[3]Department of Cybernetics, University of Hradec Králové, Czech Republic

Sustainability considerations are driving energy generation from fossil fuels to renewable sources. Grid infrastructure will be destabilized if these new resources are not coordinated properly. Transactive Energy (TE) is a coordination framework that uses economic and control mechanisms to dynamically balance supply and demand across the entire electrical infrastructure. Transactive Renewable Energy eXchange (T-REX) is presented as a way to engineer TE solutions. Agent-based computational economics is used to simulate real economic processes, which can be used to train reinforcement learning agents that will eliminate human involvement and achieve dynamic balancing in real-time. As a proof of concept, a virtual community test bench was set up using real smart home profiles collected in the Seattle region. Three sets of simulations are performed, with energy storage and trading capabilities progressively added. Economic analysis shows that the prices of energy exchanged within the community reflects the balance of supply and demand. Agents successfully used this price signal to utilize energy storage. This increased income for all participants and improved voltage stability, demonstrating that economic processes alone can be sufficient for TE. Without relying on prohibitively expensive power flow information, systems similar to the proposed test bench can be deployed inexpensively at scale.

***Index Terms*—Artificial intelligence, Computer aided engineering, Energy trading, Electricity markets, Energy storage, Load management, Power system economics, Power system modeling, Power system simulation, Simulation software, Solar energy, Market design, Microgrid, Smart grid, Trading networks, Transactive energy**

I. Introduction

Recent technological breakthroughs and sustainability considerations are changing the nature of electric power systems. The well-known shift from coal and natural gas power generation to renewable energy sources (RES) is a trend that is expected to help lower the global carbon emissions. However, this shift is not without consequences. The highly intermittent nature of RES brings operational challenges that the current grid infrastructure was not designed to handle. As a result, phenomena such as voltage fluctuations, reverse power flow, and degraded power quality [1] [2] are expected to be more frequent if RES and other distributed energy resources (DERs) are not properly integrated into the grid. Otherwise, operational detriments may overcome environmental benefits, and make RES and DERs less appealing and slow their adoption.

The energy transition is highly dependent on the engineering and deployment of flexible, robust, and adaptive energy management systems. Transactive Energy (TE) is a framework that encapsulates this idea. The GridWise Architecture Council (GWAC) defines TE as "a set 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." [3]. Although this definition is great at a high level view, it is too broad to be useful to develop specific solutions and standards from. Because of this, there have been a vast variety of TE schemes proposed over the recent years. Having a variety of solutions to choose from is only great if there exist standard methodologies for evaluating and comparing the efficacy of these schemes. However, the only way to evaluate TE schemes right now is to deploy them as pilot projects, which can be risky, slow, expensive, and complex. These issues greatly limit the number of schemes that can be tested. Furthermore, even pilot projects may be incomparable to each other depending on deployment parameters, such as region, size, demographic, etc. These challenges have made it very difficult for TE to move beyond a few demonstration projects for more than a decade.

In an effort to streamline and accelerate the research and development of deployable TE systems, we developed the Transactive Renewable Energy eXchange (T-REX), a framework that uses modern hardware and software to enable the rapid prototyping of realistic and deployable TE systems. The article is organized as follows. Section II provides a review of the current state of TE and other contemporary energy management techniques, and summarizes the key challenges yet to be solved. Section III introduces T-REX, and details its design philosophy, architecture, and major components. Section IV presents our proposed TE configuration, codenamed Test Bench One (TB-1). Section V performs case studies of TB-1, and shows the types of simulations and analysis that can be performed. Finally, conclusions are drawn, weaknesses of the work so far are identified, and studies to be presented in subsequent articles are foreshadowed.

II. Related Work

A good starting point to gain a better understanding of TE is to review recent developments in the area and learn from what worked, what did not, and discover the challenges that need to be addressed.

Surveys by Chen et al. [4] and Abrishambaf et al. [5] provide high level views of demand response (DR) programs and recent TE trends. Chen et al. find that DR programs can generally be classified into two categories: incentive-based, and price-based. Both are designed to drive customer behaviour changes, although specific implementations vary. Price-based approaches, such as time-of-use (TOU) pricing, try to match electricity prices with the overall load on the grid, dissuading customers from using electricity when prices are high, and encouraging usage when prices are low. The theoretical advantage is that the price signals will cause some loads to be time-shifted, making supply and demand more even throughout the day. However, the practical weakness of this approach is that not all customers are flexible enough to participate in load-shifting.

In contrast to contemporary DR, TE has the potential to be more flexible and adaptable to customer needs. Abrishambaf et al. [5] first provide a comprehensive review of TE research trends, and then scrutinize the weaknesses that need to be addressed. The authors conclude that most research in TE focuses on mathematical models and formulations, while paying little to no attention to practical implementation details. They also note that adequate simulation platforms and tools are required to properly confront the practical challenges of implementing TE, such as implementation costs, infrastructure requirements, networking and communication performance, physical and cybersecurity considerations, and electrical grid conditions. Finally, of the few TE system that were implemented, most demonstrated wide gaps between expectations and results. This finding highlights the need for proper simulation and emulation tools for technical verifications during the design phase to prevent failures in the implementation phase.

Two prominent directions of TE research are transactive control and networking technologies. Transactive control (TC) is a framework that seeks to integrate user preferences into grid operations better than DR programs. It results in fine-grained price signals that users should respond to produce optimal power flow. A variety of different TC strategies have been proposed, often with very specific focuses. Hu et al. [6] propose an aggregator-based optimization approach that generates charging/discharging schedules for electric vehicles (EVs). A simulation was performed on a Danish distribution network to show decreased line congestions and voltage violations. Similarly, Nazir et al. [7] use an aggregator-based model. However, they incorporate it into a model predictive control (MPC) framework to both calculate optimal price signals, and to control thermostatically controlled loads (TCLs) and storage devices to decrease power oscillations at substation feeders. Soarez et al. [8] introduce a comparable, aggregator-based approach using a dual decomposition algorithm. Notably, this work had a field test performed to validate the algorithm.

Networking technologies became a main focus in TE following the rise of popularity of blockchains and distributed ledgers. In particular, peer-to-peer (P2P) trading and local energy markets are prominent themes in contrast to aggregator-based approaches for TC. Siano et al. [9] evaluate the potential of blockchains in TE, and discuss possible approaches and challenges. Zhang et al. [10] perform case studies on theoretical P2P exchanges using game theory, and show a reduction of energy exchange between the Microgrid and the utility grid. Local energy balance could potentially be achieved with a higher diversity of generation and load profiles. Morstyn et al. [11] presents a bi-lateral contract network for P2P markets, where only local agent decisions and agent-to-agent communications are required to perform distributed price-adjustments.

While the progress of TE research and development is exciting, research and practical challenges must be addressed in order to accelerate the implementation of real TE systems. The current state of TE research is very fragmented, and even though the vast majority of related research conclude that TE can improve the grid in some way, publications often use vastly different setups and experimentation strategies that are incompatible with each other. Not only does this make it difficult to compare the efficacies of different schemes, it is also hard to judge whether benefits found are specific to the setups, or applicable to more general scenarios. The lack of practical considerations stated by [5] must be reiterated, as TE schemes are only valuable if they can be easily implemented in the real world.

III. Transactive Renewable Energy Exchange (T-REX)

The previous section attributed one of the major roadblocks TE progression to the disconnect between theory and practice. T-REX was designed with the intention to bridge this gap, but also out of necessity due to the extreme difficulty of rapid prototyping TE schemes via pilot projects. The project source can be found on GitHub [12].

A. System Architecture

The architecture of T-REX focuses on enabling and enforcing modularity and practicality. This allows a variety of functional components to be built and easily combined into a TE testing environment. The underlying design allows the same code to be used in both simulation mode and deployment, and streamlines the transition from test environments to the real world. In order to build testing environments that closely emulate the real world, modules in the assembly run as independent processes in parallel. The modules are tied together by a scalable and efficient messaging engine.

Figure 1 shows the simplified diagram of the current architecture. It is built on top of socket.io [13], and closely resembles online chat apps such as Discord and Slack. Like in these apps, a server is necessary to handle client management and message relaying. In deployment scenarios, multiple server instances can be tied together to achieve horizontal scalability and resiliency. Messages are further organized by namespaces and rooms, and availability can be customized depending on requirements. For example, the simulation namespace is used to augment T-REX environments from deployment mode into simulation mode. The functional modules are built as socket.io clients. The words “module” and “client” are used interchangeably in the context of T-REX. Three main types of clients have been implemented, as shown on the architecture diagram. Each client is functionally distinct. Participants are in charge of energy trading and managing energy resources that are directly accessible. Market facilitates the discovery and exchange of energy between participants. Simulation controller augments a deployment environment into simulation mode, and can also perform advanced functions such as training curriculums. The APIs for inter-client communications are carefully designed to be as generic as possible to avoid limiting module designs to overly specific archetypes. Client types and namespaces are not restricted to the ones shown, and new ones should be created to accommodate changing trends. For example, traffic data clients can be added to enable self-driving electric vehicles (EV) as mobile participants to physically move energy between regions. This flexibility will help emerge more ways to transition the static grid into a more dynamic future.

B. Simulation System

The modular nature of the T-REX architecture naturally leads to agent-based modeling and multi-agent simulations, which are useful for studying complex systems consisting of independent, intelligent interacting agents. Agent-based modeling has garnered interest for use in the electricity system for both traditional markets [14] and transactive energy [15] [16]. A few agent-based simulation tools for power are available, with GridLab-D [17] being the most functional and comprehensive. T-REX improves upon these tools in two ways: first, because T-REX is written in Python, modern machine learning frameworks such as TensorFlow or PyTorch can be used to develop highly complex agents. Second, T-REX focuses on simulating true economic processes, rather than deriving transactions from optimal power flow simulations. This allows the TE market to perform its true function as an enabler of dynamic balancing of supply and demand. Agent-based computational economics (ACE) [18] and related works provide deeper insight into this topic. Crucially, the market in ACE is a fitting environment for reinforcement learning (RL) [19], as shown in Figure 2. This synergy gives RL researchers complex and realistic environments to develop agents. These agents can in turn be used to design and develop more flexible and automated TE solutions, forming a positive feedback cycle.

IV. Proposed Implementation (TB-1)

TB-1 (test bench one) is the implementation of TE built with T-REX that uses smart agents and ACE principles to achieve dynamic balance of supply and demand, rather than deriving pricing schedules from optimal power flow (OPF). TB-1 consists of two complementary components:

- localized, real-time transactive energy market.
- AI energy trading and management agents as active participants.

Choosing a market-based approach over OPF-based solutions is mainly due to practical considerations. Because the majority of distribution systems do not have supervisory control and data acquisition (SCADA) systems, acquiring high-resolution power data in real-time is very difficult. In contrast, agents in a market only need to acquire their own power profiles in order to enter the market. This can be achieved easily and inexpensively with smart meters and other energy measurement systems.

A. Micro-Transactive Energy Market (MicroTE)

MicroTE is the market component of TB-1, a highly localized market intended to maximize utilization of locally available energy resources. The main difference between MicroTE and the current market is that MicroTE is a localized market designed to be built and scaled from the bottom-up, rather than top-down. Lezama et al. [20] suggests that by facilitating energy trading, local markets (LMs) can increase RE penetration and lower costs. This hypothesis will be further tested in section V.

Because markets implemented in T-REX are entirely software based, the market mechanisms must be explicit and specific, leaving no room for misunderstanding. A description of the current set of mechanisms for MicroTE follows:

1) It can be safely assumed that the grid is always available and can be interacted with through common net-billing rules. In the current iteration, buying energy from the grid for costs \$0.1449/kWh, and selling earns \$0.069/kWh. These prices are in line with retail electricity prices in Alberta as of time of writing.
2) The local market has two energy pools: one for dispatchable sources, such as battery energy storage systems (BESS), and one for non-dispatchable sources, such as photovoltaics (PV). This is intended to better distinguish the source of energy, and to make it possible for the value of dispatchability to emerge.
3) Auctions settle for energy to be delivered during the one-round period from the end of the current round. However, the delivery period can be parametrically adjusted during run-time for future design explorations.
4) During the current round, participants submit bids and asks for energy to be delivered during or beyond the next delivery period.
5) A modified double auction system is used to settle trades: bids/asks are settled pairwise, with bids sorted from the highest to lowest, and asks in reverse. Settlement only occurs if bid price is greater than or equal to ask.
6) Bid/ask quantities can be partially settled.
7) The settlement price is the average of bid and ask pairs to be settled. Additional settlement algorithm modules will be built for future exploration as necessary.
8) For hardware integration reasons, bid/ask quantity must be an integer multiple of 1 Wh to allow direct use of the watt-pulse function of most smart-meters.
9) During the delivery period, if a seller is in short supply, they must financially compensate for the shortage at net metering prices. If batteries are available, the seller has the option to compensate by discharging their batteries, for all or part of the shortage during this period.
10) During the delivery period, if a buyer settled for more energy than used, the buyer must still pay the seller for the unused energy at the settlement price.

Tests performed so far suggest that this set of mechanisms provides sufficient scenario coverage. Changes will be made as needed to address unforeseen scenarios if and when they appear. Some parameters, such as delivery time interval, are

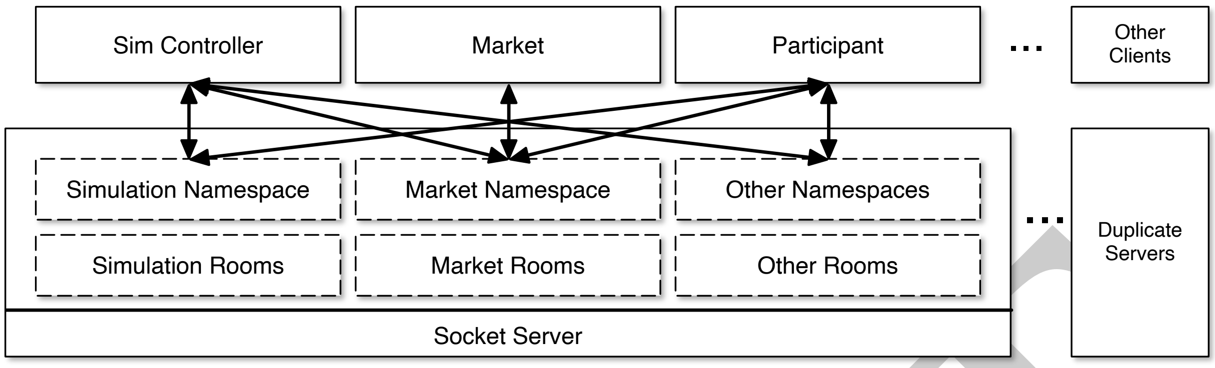


Fig. 1: Simplified T-REX V3 Architecture Diagram

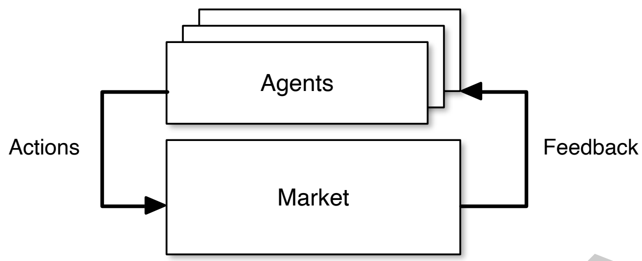


Fig. 2: ACE Process Diagram

intentionally left unrestricted to provide maximum exploratory opportunities for agents during training.

B. Agents

One of the most difficult aspects to predict in TE is the effect on human behaviour. With TB-1, a deliberate decision was made to assume the worst case scenario: humans will not respond to any TE schemes. Instead, the only way to actively modify energy profiles is through BESS. By removing humans from the control loop, system design can be simplified, and validation can be more reliable.

Agents act as an intermediate layer between humans and the energy system. Their primary goal is to maximize the value of energy by using all accessible energy resources. The agent's market interaction is defined by setting a small set of parameters (bid/ask, price, quantity, and source) each settlement round. If a BESS is available, the agent can schedule the quantity of energy to be charged or discharged during a delivery period. A common set of information is returned from the market to all agents independent of learning algorithm. Namely, the agents receive simplified copy of relevant transactions after each delivery round. Each transaction contains the quantity, price, and source of energy, as well as supplementary information such as time of creation and time of consumption. It is up to the designers to convert this information into formats suitable for the algorithms they choose to implement. For example, the agents used in the experiments described in this article calculate the per-unit profit and cost of energy transacted for learning.

C. Event Flow

The basic ACE/RL process diagram in Figure 2 is expanded with a few key T-REX function blocks to form Figure 3. T-REX can function in both real-time mode and simulation mode with slight differences. Real-time exclusive events and functions are highlighted in amber, and simulation exclusive events and functions are highlighted in cyan.

In real-time mode, the market has control of timing, therefore timeouts are used to terminate each round regardless of whether agents manage to complete their trading logic in the allotted time. In simulation mode, the simulation controller has control of timing. Furthermore, all agent functions in the main loop are guaranteed to be complete before advancing to the next timestep. Not shown on are the optimal functions that allow training-related parameters to be precisely controlled by the simulation controller.

V. Experimental Design

The primary goal of the experiments conducted is to test whether a real market is a viable and sufficient approach to coordinating energy in real-time. The secondary goal is to verify the claims made by Lezama et al. [20] that energy trading through LMs can increase RE penetration and lower costs. The agent used in the experiments is an expert-designed system that uses moving average crossovers to determine buy and sell triggers, a popular technique used in stock trading. The complete set of details can be found on the project repository [21]. A brief description of the experimental setup is as follows.

For the experiments, a virtual community is set up using real load and generation data collected from smart homes in the Seattle region. The resolution of the data is between 1 minute (recently acquired) and 15 minutes (older). The 15-minute interval data is converted to 1-minute intervals by splitting the amount of energy metered over 15 minutes to 15 equal portions. Participants in the virtual community are connected using the residential sub-circuit of the North American low voltage benchmark circuit [22]. The circuit is recreated as closely as possible using the given parameters, and power flow simulations are performed using OpenDSS through the OpenDSSDirect Python extension [23].

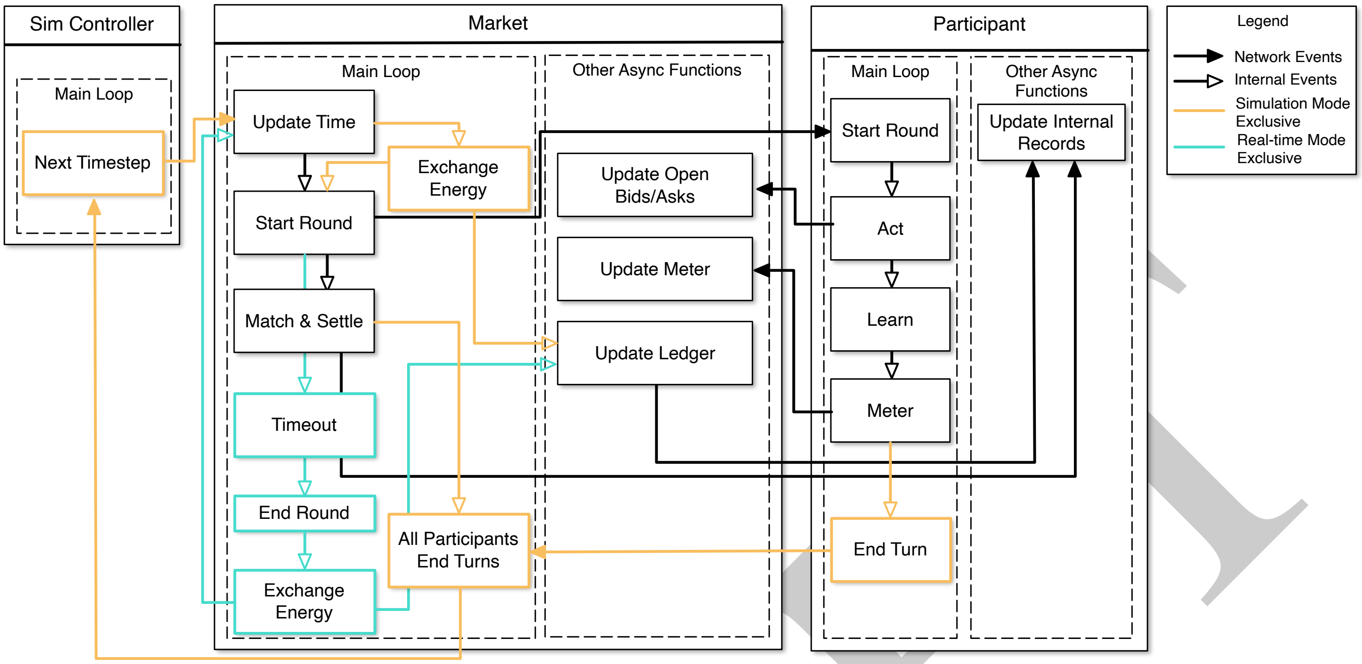


Fig. 3: TB-1 Event Flow

TABLE I: Participant profile characteristics (all units are kW)

Participant	Max Generation	Min Load	Max Load
R5	9.42	0.24	7.38
R6	10.44	0.48	7.68
R7	4.32	0.24	5.64
R8	6.24	0.30	7.20
R9	6.24	0.12	7.02
R10	0	0.06	7.62
R11	0	0.30	8.40
R12	7.68	0.18	7.14
R13	5.88	0.18	8.28
R14	5.28	0.18	8.82

To fit the benchmark circuit and to establish a baseline for comparison, 10 out of the 53 profiles were selected. July of 2018 was chosen as the simulation period. This is the period of the year with the most intense solar radiation, which would reflect the worst impact of PVs on system voltages. A random search was performed to find the right combinations of participants and locations that would result in both partial PV penetration, as well as voltage violations on the circuit (>1.04 p.u.). Power flow simulation was also performed for the scenario with no PV penetration to verify that the system normally operates within specifications. A summary of the key properties of the participants are shown in Table I. Participant names have been modified to correspond to the node names of the benchmark circuit.

Experiments are conducted progressively in three stages. Stage-1 (PV-only) is designed to test the ability of the agents to utilize MicroTE to learn a table of prices that reflect the perceived supply and demand for each minute of the day. During this stage, DERs only consist of PVs, therefore no opportunities are available to shape power profiles. The ability to learn prices is necessary to utilize storage. BESS are introduced to the two participants that do not have generation (R10, R11) starting from stage-2. The BESS specifications mimics two Tesla Powerwalls (27kWh usable capacity, 10kW constant charge/discharge, 90% round trip efficiency). For stage-2, the agent is limited to buying the excess solar energy on the market for self consumption only. This tests the viability of moving average crossover as a way to find market entry points. Stage-3 (BESS-2-ways) enables the agent to also sell energy stored in the battery back to other participants.

Three simulations are performed for each stage for consistency. For each simulation, learning is continuously performed for at least 100 episodes to ensure that the system remained in the Nash equilibrium for at least 50 episodes. This also ensures that the learned pricing tables fit to the simulation time period. Over-fitting is a desirable outcome for these experiments for consistency and repeatability. Training agents that can generalize trading logic using T-REX is a major topic planned for the near future.

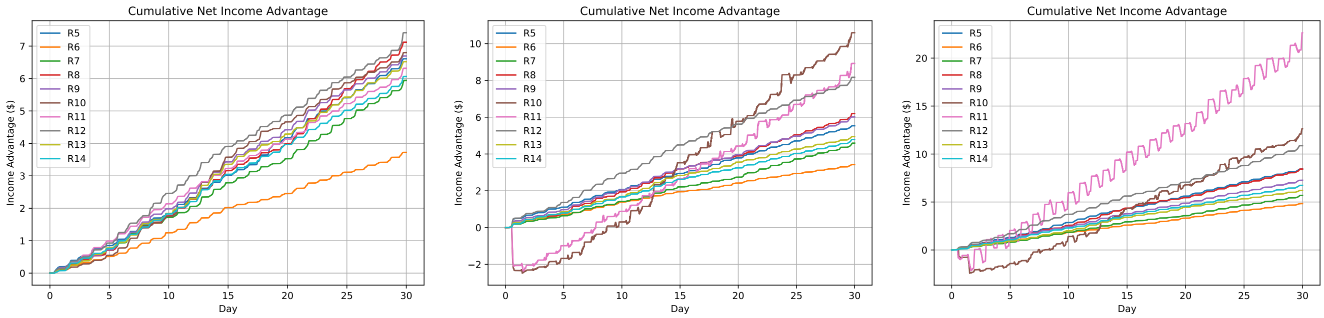
A net-billing equivalent simulation is run alongside every MicroTE simulation as a baseline for comparison. Financial and power analysis will be performed and compared against the baseline.

VI. Results and Discussion

A. Financial Advantage

The most important aspect to analyze is the relative net income compared to the baseline. Any TE scheme that cannot financially outperform the baseline over a billing cycle has no chance of real world adoption, regardless of improvements in other areas. In our case, all participants should outperform the baseline as long as the agents learn to use MicroTE to exchange energy within the community.

Figure 4 shows the cumulative income advantage over the baseline for all three simulation stages. As expected, all the



(a) Simulation Stage-1 (b) Simulation Stage-2 (c) Simulation Stage-3, Nash 2

Fig. 4: Income advantages

participants were able to outperform the baseline at the end for all the simulations.

Figure 4b shows the cumulative income advantage for stage-2. The first observation is that both BESS equipped participants under-performed the baseline for the first 8 to 10 days. This is due to the fact that BESS are initialized as empty, thus incurring additional load and cost upfront. The BESS equipped participants ultimately outperformed stage-1 at the end, however, other participants under-performed. The most likely reason for this phenomenon is that the BESS resulted in less trades during sunrise and sunset, where solar energy is more expensive than in the middle of the day. This can be seen when comparing Figure 5c to Figure 5a.

Stage 3 increased the market dynamics by allowing BESS to compete as a source of energy. This new dynamic caused two separate equilibrium states to appear out of the three simulations performed. The first state is similar to the results for stage-2 and therefore not shown. The second state is shown in Figure 4c. In this simulation, the performance of all the participants are greater than or equal to stage-1. R11 in particular shows dominating performance, and was consistently able to arbitrage community generated solar. R10 could not keep up with the competition in the later episodes and defaulted to only using BESS for self consumption.

It is clear from these results that the overall value of community generated solar increased due to the introduction of BESS into the system, and points to positive social implications. Currently, the only compelling use case for installing a home BESS is to supplement roof top PV to increase self sufficiency. However, the additional upfront cost of such a system may not be economically viable. By granting all participants access to all available DERs in a community through MicroTE, the benefits of the DERs can be distributed to everyone in the local area.

B. Settlement Prices

Settlement prices analysis can provide a more global view of whether strategies were formed that result in settlement prices that reflect the balance of supply and demand.

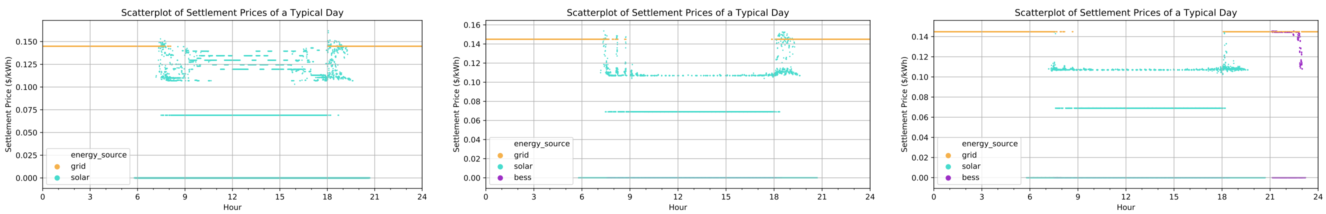
Figures 5a, 5b, 5c show the settlement prices and the energy profiles for a typical day for each simulation stage. Because MicroTE can distinguish the source and type of energy, the settlement prices are color coded accordingly. The orange dots at \$0.1449 represent the energy bought from the grid, and the blue dots at \$0.069 represent the solar energy that is sold to the grid. Energy settled for \$0 represent self consumption. All other dots represent transactions between participants through MicroTE. All three figures show strong evidence that settlement prices reflect the balance of supply and demand. It can be seen that prices start high and decrease during sunrise, stay at equilibrium value during the day, then rise again during sunset. It should be noted that an equilibrium price failed to emerge for stage-1. Currently planned future study, which will compare and evaluate multiple learning algorithms under the same settings, will show whether this phenomenon is due to the learning approach, or other factors in the system

Closer examinations of the figures show that some energy exchanges settled above the price of purchasing energy directly from the grid. These illogical trades are artifacts of the learning algorithm, which was intentionally designed to not use any grid price information as a means to test learning stability. The learned prices were able to remain in a reasonable range under these conditions, which makes it safe to include caps based on grid prices in future iterations of the algorithm.

C. Power Flow Analysis

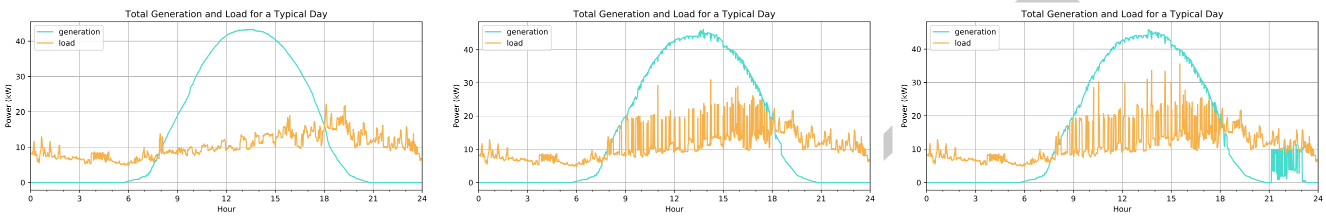
Power flow simulation is performed to check whether MicroTE can increase RE penetration. This is done by comparing the node voltages for all three simulation stages.

Figure 7 shows the results of power flow analysis. The node voltage snapshots for every minute of each simulation are represented as box plots. As a reminder, the profiles and locations were initially chosen so that the node voltages would be out of operating specifications. It can be clearly seen that multiple voltage violations occurred for every node in the baseline case. In contrast, no voltage violations occurred in stage-2, which is a clear sign of increased RE hosting capacity. Surprisingly, node voltages for stage-3 worsened compared to stage-2. Figure 5c shows slight injections from the BESS into the system during the middle of the day, which is the likely source of the degraded performance. This points to flaws in the control algorithm, and was somewhat expected, as the trigger condition for selling was tuned to be highly aggressive in order to maximize exploration. Ultimately, these results confirm that



(a) Simulation Stage-1 (b) Simulation Stage-2 (c) Simulation Stage-3

Fig. 5: Settlement Prices on July 17, 2018



(a) Simulation Stage-1 (b) Simulation Stage-2 (c) Simulation Stage-3

Fig. 6: Aggregated Community Generation and Load on July 17, 2018

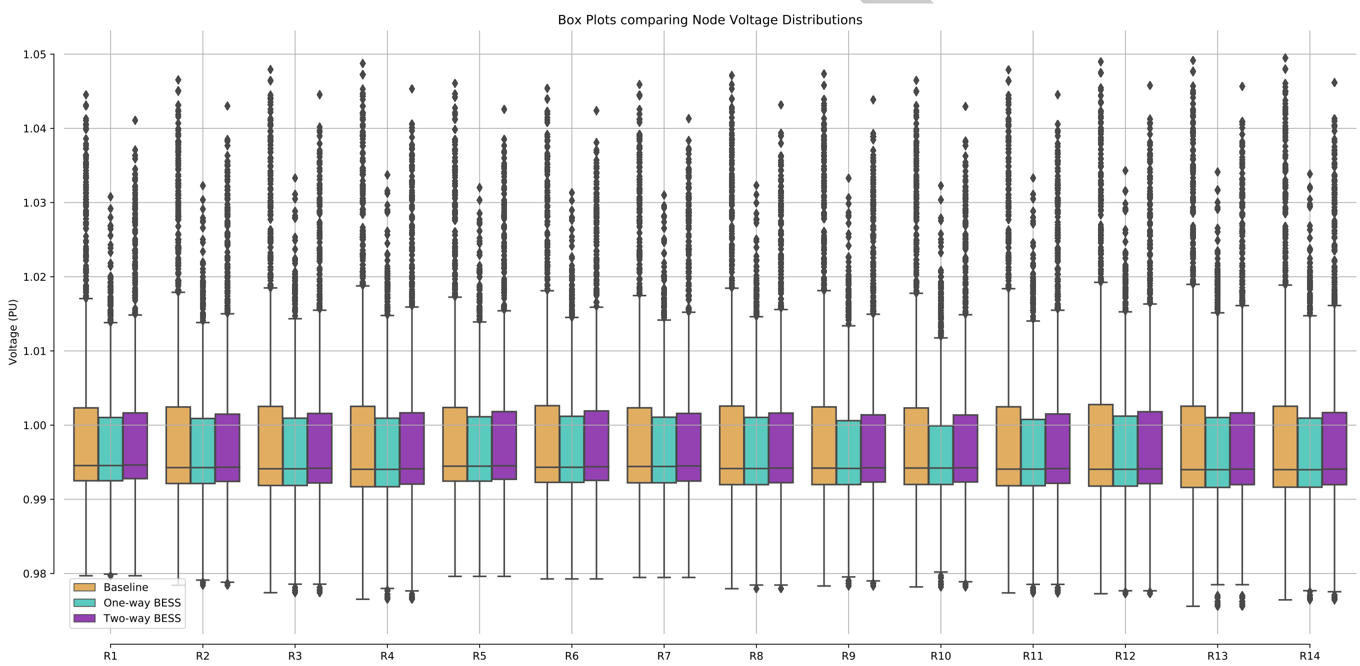


Fig. 7: Comparisons of node voltage distributions for all simulation stages

LMs, with the right mixture and access to DERs, can increase RE hosting capacity. The ability of MicroTE to achieve this without any power information validates the hypothesis that economic process alone can be a viable and sufficient approach to coordinating energy in real-time.

VII. Conclusions

TE is defined as "a set 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 work presented in this article is in pursuit of a robust, flexible, and practical TE system. The proposed solution relies purely on market principles, in contrast to OPF-based approaches.

T-REX was built to aid the engineering of this solution. It uses ACE principles to simulate a true economic process, and combines with RL to produce highly sophisticated energy trading and management agents. Because simulation mode is a simple augmentation of deployment mode, the simulation environment is realistic and includes all the system level nuances unseen in other simulation systems. This also ensures that code written for simulations is readily deployable, thus streamlining the engineering process.

As a proof of concept, a test bed (TB-1) was set up as a virtual community using real smart home profiles collected in the Seattle region. An expert designed system was used for energy trading and management to remove the complexities involved with machine learning. Three sets of simulations were performed, with BESS and trading capabilities progressively added.

Economic analysis clearly showed that the value of energy exchanged within the community reflected the balance of supply and demand. This dynamically generated price trend was then used by the agents to utilize BESS to increase their potential income. This pursuit for better value resulted in both increased income for all the participants, as well as improved voltage stability.

TB-1 demonstrated that economic process alone can sufficiently enable the dynamic balance of supply demand in a community with a mixture of DERs. Because TB-1 does not rely on power flow or delegate grid management to end-users, deploying a similar system in the real world can be inexpensive and reliable.

VIII. Future work

Given the results shown in this article, multiple avenues of follow-up work can be performed. The first is to iterate upon TB-1 by testing different settlement algorithms, along with improved logic for the expert designed trader. The second is to test the scalability of MicroTE by including the commercial subnetwork, and see if additional value can be gained through the same economic process. Finally, a major focus will be placed on developing RL agents. With the right design, these agents should be able to far outperform any expert designed system, making it possible and practical to transition into a fully distributed and automated grid.

IX. Acknowledgements

This work has been supported by the Natural Sciences and Engineering Research Council of Canada (NSERC) grants and by the Canada First Research Excellence Fund (CFREF) under the Future Energy Systems research initiative at the University of Alberta. The authors would like to thank Dr. Andrew Leach and Dr. Tim Weis for their advice on the operation of electricity markets. Members of ENTAIL research lab Daniel May and Peter Atrazhev participated in many fruitful discussions of the approach presented in this contribution.

References

[1] S. M. Ismael, S. H. A. Aleem], A. Y. Abdelaziz, and A. F. Zobaa, "State-of-the-art of hosting capacity in modern power systems with distributed generation," *Renewable Energy*, vol. 130, pp. 1002 – 1020, 2019.

[2] T. O. Olowu, A. Sundararajan, M. Moghaddami, and A. I. Sarwat, "Future challenges and mitigation methods for high photovoltaic penetration: A survey," *Energies*, vol. 11, no. 7, 2018.

[3] D. Forfia, M. Knight, and R. Melton, "The view from the top of the mountain: Building a community of practice with the gridwise transactive energy framework," *IEEE Power and Energy Magazine*, vol. 14, no. 3, pp. 25–33, 2016.

[4] S. CHEN and C.-C. LIU, "From demand response to transactive energy: state of the art," *Journal of Modern Power Systems and Clean Energy*, vol. 5, no. 1, pp. 10–19, 2017.

[5] O. Abrishambaf, F. Lezama, P. Faria, and Z. Vale, "Towards transactive energy systems: An analysis on current trends," *Energy Strategy Reviews*, vol. 26, p. 100418, 2019.

[6] J. Hu, G. Yang, C. Ziras, and K. Kok, "Aggregator operation in the balancing market through network-constrained transactive energy," *IEEE Transactions on Power Systems*, vol. 34, no. 5, pp. 4071–4080, 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, no. 5, pp. 4060–4070, 2019.

[8] A. Soares, O. De Somer, D. Ectors, F. Aben, J. Goyvaerts, M. Broekmans, F. Spiessens, D. van Goch, and K. Vanthournout, "Distributed optimization algorithm for residential flexibility activation—results from a field test," *IEEE Transactions on Power Systems*, vol. 34, no. 5, pp. 4119–4127, 2019.

[9] P. Siano, G. De Marco, A. Rolán, 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, no. 3, pp. 3454–3466, 2019.

[10] C. Zhang, J. Wu, Y. Zhou, M. Cheng, and C. Long, "Peer-to-peer energy trading in a microgrid," *Applied Energy*, vol. 220, pp. 1 – 12, 2018.

[11] T. Morstyn, A. Teytelboym, and M. D. Mcculloch, "Bilateral contract networks for peer-to-peer energy trading," *IEEE Transactions on Smart Grid*, vol. 10, no. 2, pp. 2026–2035, 2019.

[12] S. Zhang, "Trex-core." https://github.com/trex-ai/TREX-Core, 2020.

[13] D. Arrachequesne, "Socket.io."

[14] L. Tesfatsion, "Chapter 13 - electric power markets in transition: Agent-based modeling tools for transactive energy support," in *Handbook of Computational Economics* (C. Hommes and B. LeBaron, eds.), vol. 4 of *Handbook of Computational Economics*, pp. 715 – 766, Elsevier, 2018.

[15] H. S. V. S. K. Nunna and D. Srinivasan, "Multiagent-based transactive energy framework for distribution systems with smart microgrids," *IEEE Transactions on Industrial Informatics*, vol. 13, no. 5, pp. 2241–2250, 2017.

[16] Z. Vale, T. Pinto, I. Praça, and H. Morais, "Mascem: Electricity markets simulation with strategic agents," *IEEE Intelligent Systems*, vol. 26, no. 2, pp. 9–17, 2011.

[17] D. P. Chassin, J. C. Fuller, and N. Djilali, "Gridlab-d: An agent-based simulation framework for smart grids," *Journal of Applied Mathematics*, vol. 2014, 1 2014.

[18] L. Tesfatsion, "Agent-based computational economics: growing economies from the bottom up.," *Artificial Life*, vol. 8, no. 1, pp. 55–82, 2002.

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

[20] F. Lezama, J. Soares, P. Hernandez-Leal, M. Kaisers, T. Pinto, and Z. Vale, "Local energy markets: Paving the path toward fully transactive energy systems," *IEEE Transactions on Power Systems*, vol. 34, no. 5, pp. 4081–4088, 2019.

[21] S. Zhang, "Trex-journal-1." https://github.com/sd-zhang/TREX-Journal-1, 2020.

[22] 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.

[23] D. Krishnamurthy, "Opendssdirect.py." https://github.com/dss-extensions/OpenDSSDirect.py, 2017.