2022 10th Workshop on Modelling and Simulation of Cyber-Physical Energy Systems (MSCPES) | 978-1-6654-6865-7/22/$31.00 ©2022 IEEE | DOI: 10.1109/MSCPES55116.2022.9770159

Evaluate Peak Usage Reduction of a Multi-round Real-time Pricing Model Using Co-simulation

Chenli Wang
National Inst. Of Standards and Technology
Gaithersburg, MD, USA
chenli.wang@nist.gov

Thomas Roth
National Inst. Of Standards and Technology
Gaithersburg, MD, USA
thomas.roth@nist.gov

Cuong Nguyen
National Inst. Of Standards and Technology
Gaithersburg, MD, USA
cuong.nguyen@nist.gov

***Abstract*—The widespread deployment of distributed energy resources (DERs) makes energy demand and generation more dynamic than before. The most prominent existing tariffs systems, flat-rate and time-of-use (TOU), are not designed to let retail prices reflect varying power demand and supply. New dynamic pricing structures have been developed to reveal the fluctuating cost of energy so that consumers can adjust their power consumption plan based on the time-varying utility rate. However, the validation of such a real-time pricing system is still a problem since physical testing is costly and time-consuming. To address this gap, this work explores a co-simulation platform to assess the peak-shaving impact of a dynamic pricing scheme in a Transactive Energy (TE) grid.**

This work devised a Heating, Ventilation, and Air Conditioning (HVAC) system control strategy to adjust the heating/cooling setpoint based on utility price. To validate this price-driven algorithm, a building energy predictor was developed to predict the next-hour energy consumption based on HVAC setpoint and environment conditions. In addition, a utility simulator was also devised to publish the next two-hour energy price based on current net demand and utility capacity. All these aforementioned entities were integrated with the building simulation software, EnergyPlus, via an open-source co-simulation platform initially developed from the National Institute of Standards and Technology (NIST). The energy profiles and cost for utility were compared between a case with the proposed model and a baseline case that used the flat-rate pricing system.

Keywords—real-time price, demand response, building energy management system, co-simulation, high level architecture

I. Introduction

Transactive Energy (TE) has been considered as one of the technologies that could reduce peak load and improve the reliability of the power system. TE is a broad term that has been defined as “A system of economic and control mechanisms that allows the dynamic balance of supply and demand across the entire electrical infrastructure using value as a key operational parameter.”[1], where the term “value” here primarily means retail energy price. TE aims to make the retail energy price reflect the actual varying cost of generating/supplying energy. Under TE scheme, customers would change their energy consumption behavior based on the retail price, so the energy demand would be better reflect retail price, and the peak demand would be reduced.

Some utility companies have implemented Time-of-Use (TOU) tariff methods in which retail prices are fixed seasonally based on the typical peak and off-peak periods in a day. A report [2] from America Public Power Association (APPA) shows that the TOU pilot rates produced load reductions and peak shaving in California. A similar result is found in Maryland that TOU pilots reduce peak load by at least 10% in summer months (June - September) and about 5 % in non-summers months (October - May) [3]. Compared with the traditional flat-rate pricing, TOU pricing is one step closer to showing the actual cost of supplying energy. However, TOU pricing still has limitations: 1) The price ratio between the peak-demand and off-peak periods is slight. For example, the price ratio in California is 1.4 in summer and 1.03 in winter [4]. An additional financial benefit may need to encourage more customers to enroll in a TOU rate plan and alter their energy usage habits. With more participants, the TOU rate plan would be able to balance the daily demand better. 2) The TOU pricing methods are based on a predefined schedule of peak and off-peak periods. To ensure the actual demand peaks are always inside the scheduled peak period, utility companies tend to design a longer high-demand window. A Brattle report [5] demonstrates that more than half of recent TOU pilots have a peak period of 5 hours, which limits the use of some short-term load-shifting methods. There is a need for a more dynamic pricing system that allows retail energy price to track the actual cost and engage more people in peak-shaving behaviors.

In [6], Zehmayr et al. propose an hourly real-time pricing method that responds to the grid demand. After analyzing annual energy-usage data from more than 300,000 customers, the study shows that real-time pricing compared with flat-rate pricing can save about 13.2 percent of customers' bills. In [7], Widergren et al. demonstrate a residential TE scheme in a small community (100 households), where the retail electricity rate is updated every 5 min. Each building sends an energy consumption plan to an operation center. After receiving all the bids, the operation center will find the clearing price for the next 5 minutes and broadcast it to all the users. This approach features automated decision-making in a TE scheme. The test result shows the responsive HVAC load is reduced during a 4-hour critical peak pricing event.

Prior works in this area focus on publishing a real-time tariff based on the users' energy consumption plan and assume consumers follow their original plan. Nevertheless, people may change their minds after receiving the clearing price because the energy price is higher or lower than their expectations. These changes may cause some unexpected demand spikes or unnecessary waste. Due to the limited controllability of home appliances (e.g., dishwasher, washer, and dryer), residential customers cannot frequently turn these appliances on/off based on the dynamic retail price. This work envisions a hourly multi-round real-time pricing scheme that requires users to report their consumption plan after every time they receive a new price from utilities. The utilities update and broadcast a new energy price based on users' new demand bids. This negotiation process keeps going on until an optimal clearing price is found or the predetermined minimum/maximum price is reached. Eventually, utilities benefit from peak-shaving, and consumers receive monetary incentives by shifting load to off-peak periods. The multi-round pricing system considers the benefits of both electricity service providers and their customers.

Physically testing such a power system is costly and time-consuming. A simulation tool is needed to validate the effectiveness of energy management techniques and real-time pricing methods. Although existing building simulation software can estimate the energy load well, it cannot readily implement a new price-based HVAC control algorithm or frequently exchange information with a utility entity during the simulation. A validation tool is leveraged to overcome this limitation based on the Universal Cyber-Physical Systems environment for Federation (UCEF) [8], an open-source co-simulation platform developed by the National Institute of Standards and Technology (NIST). A building simulator, EnergyPlus [9], is also integrated to effectively evaluate the actual building energy consumption at each time step. Among the different building simulation software, EnergyPlus offers the most comprehensive platform to model residential and commercial buildings, considering environmental information and detailed building parameters (e.g., floorplan, material, location, and orientation). A building energy management simulator with price-based load-shifting algorithm is also explored and integrated to optimize the thermostat setpoints and report energy demand bids to utilities. A multi-round hourly real-time pricing scheme is implemented to provide complete information (e.g., energy-saving and monetary incentive) to users and engage more people in peak load reduction behavior.

This simulation method is adaptable to incorporate additional considerations, including new HVAC control algorithms, new pricing methods, and control strategies for other smart appliances. This work can also be repeated and expanded to different building models or locations in the future, and can contribute to developing the TE pricing scheme and price-based energy management strategies for grid-interactive buildings.

II. Materials and Methods

A. Building Simulator

Buildings are responsible for about 70 % of the load on today's grid, which significantly affects the shape of the electric load [10]. However, the energy consumption in a building is hard to estimate since it incorporates a lot of factors, such as floorplan, wall structure, building location, HVAC loads, and weather information. This work uses EnergyPlus [9] as the building simulator to evaluate the energy consumption at each timestep. The building model used in this work is the U.S. Department of Energy (DOE) residential prototype model published in 2018 [11]. DOE provides building models for each edition of the International Energy Conservation Code (IECC). The model is based on a 2400 square foot single-family home with a heat pump heating system and a crawlspace foundation type, located in Baltimore, Maryland, USA. The model's footprint is the same, but the materials and wall structures of the model are varied to show the community's diversity. The DOE's original model uses the auto-size function of EnergyPlus to adjust the HVAC size based on different heating/cooling setpoints. In order to keep the HVAC size consistent with different setpoint schedules, a fixed HVAC size is manually selected and assigned for cooling and heating in this work. The HVAC system is controlled by another simulation entity, building energy management. All the other loads (lighting, water heater, and appliances) operate on a fixed schedule. Table 1 below lists some details of this single-family house model.

TABLE I. DETAILED SPECS OF BUILDING MODEL

Building Attribute		Quantity	Units
Number of Floors		2	-
Area		2400	Sq. ft.
No. of Zones		1	-
Cooling Capacity		3900	W
Heating Capacity		4000	W
U-factor of Window	Group 1	0.20	$W/m^2 \cdot K$
	Group 2	0.25	
	Group 3	0.30	
	Group 4	0.35	
	Group 5	0.40	
Thickness of the Sheathing in Exterior Wall	Group 1	10.0	mm
	Group 2	12.5	
	Group 3	15.0	
	Group 4	17.5	
	Group 5	20.0	

B. Building Energy Management System

Building energy management systems (BEMS) play a critical role in a TE system since it communicates with both customers and utilities. For customers, BEMS are responsible for presenting the real-time energy price and automatically optimizing users' energy usage based on price-driven peak load reduction algorithms. For utilities, BEMS needs to predict the building energy consumption in the following hours and report to the energy market so that utilities can publish a fair price to shave the peak load. Load optimization for household and energy consumption prediction for utilities are two major functions in BEMS that are introduced in the following sub-sections.

1) Load Optimization

The benefit of peak-shaving, shifting load from the peak to the off-peak period, has been actively discussed and proved in the research domain [12]. This work adopts one peak-shaving technique called pre-cooling, which suggests consumers set their cooling setpoint to a lower temperature prior to the peak-load hours and then allow the temperature to rise naturally. In [13], Xu et al. tested pre-cooling strategy in an office building. The result shows that pre-cooling can shift 80 % of the electric load due to the cooling plant from the on-peak to the off-peak period.

In the residential sector, the controllability of HVAC systems is limited. Most of them use binary on/off control. Pre-cooling may increase total energy consumption due to maintaining a larger temperature difference between indoor and outdoor. As a result, customer need to pay more by using the pre-cooling strategy with the a flat tariff system, which prevents consumers from adopting this strategy. However, with the new TE pricing system, customers will receive a monetary incentive from load-shifting, and the pre-cooling technique is able to realize the full potential of peak-shaving.

Not all buildings can use pre-cooling, because it may create a more significant demand spike in advance of expected peak hour. The price sensitivity, P_s, is introduced to separate users into the pre-cooling group and the regular operation group. The cooling policy is shown below in (1):

$$T_{cs}(t) = \begin{cases} T_c - 3℃, & if \ \frac{P'(t+1)}{P(t)} \geq P_s \\ T_c, & if \ \frac{P'(t+1)}{P(t)} < P_s \end{cases} \qquad (1)$$

where $T_{cs}(t)$ is the cooling setpoint, T_c is the regular cooling setpoint from user input. The American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) Standard 55 [14] reported that occupants feel comfortable in at least 3 °C temperature band in most indoor scenarios. This work assumes users set the cooling setpoint as their higher bound of the comfort band, allowing occupants to feel comfortable with the minimum energy consumption. In addition, 3 °C is selected as the pre-cooling offset, which means the room temperature will remain in the comfortable band during the pre-cooling period. $P(t)$ represents the energy price for the current timestep and $P'(t+1)$ is the expected price for the next timestep. Price sensitivity, P_s, is a positive number input from users that indicates when they are willing to use the pre-cooling algorithm to gain economic reward and help utilities shave the peak load. A similar pre-heating idea is explored for heating scenarios. The operation equations are listed below in (2):

$$T_{hs}(t) = \begin{cases} T_h + 3℃, & if \ \frac{P'(t+1)}{P(t)} \geq P_s \\ T_h, & if \ \frac{P'(t+1)}{P(t)} < P_s \end{cases} \qquad (2)$$

where $T_{hs}(t)$ is the heating setpoint, and T_h is the regular heating setpoint.

2) Energy Consumption Prediction

The BEMS is also responsible for predicting and reporting the energy consumption to utilities. A better energy demand prediction will help utilities recognize the demand spikes in advance and correspondingly adjust energy prices. Hence, the BEMS reports predicted energy consumption of not only the current hour but also the next hour to utilities. Three binary states affect these two energy prediction values, whether the building uses pre-cooling in the previous hour, current hour, and the next hour.

C. Utility

In a TE scheme, utilities need to publish an appropriate energy price every hour that is able to reflect the actual energy demand and supply status in the power grid. The proposed pricing model needs to predefine a default energy price, $P_{default}$, a maximum price, P_{max}, and a minimum price, P_{min}. The default energy rate should be around the current tariff so that users' total energy cost would still be in the same ballpark. The price ratio between P_{max} and P_{min} should be significant enough to engage people to shift their energy demand.

Due to the limited capability of load prediction, the BEMS cannot predict and report the detailed power demand in the next hour to the utilities. In this work, the total energy consumed over an hour is used as a proxy for the demand that must be managed. If the energy consumption prediction, $E_p(t)$ from the BEMS exceeds a threshold E_c, a constant value predefined by utilities, it is considered as the peak-usage hour. The hourly energy rate keeps at the default price until the utilities realize there would be peak-usage hour in the next hour, and the grid still has some availability in the current hour. To motivate and reward load-shifting behavior, utility will decrease the energy price in the present hour by ΔP as well as increase the expected price in the next hour by ΔP'. Users will report a new energy consumption prediction once receiving the new P(t) and P'(t+1). This negotiation process continues until the next hour is no longer a peak-usage hour, or the energy prices reach the maximum or minimum limits. Fig. 2 below shows the flowchart of this pricing model.

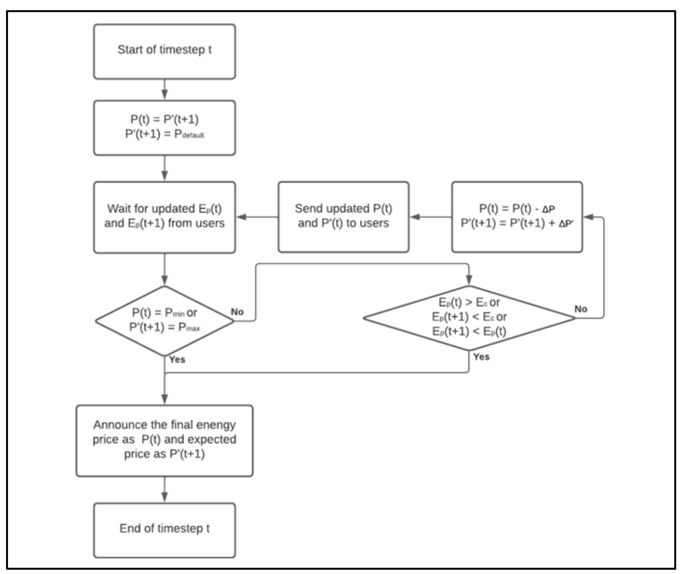

Fig. 1. Flowchart of the multi-round real-time pricing model

D. Co-simulation Platform

This work utilizes UCEF to integrate all the aforementioned simulation entities and handle time synchronization and data transfer in the network. Roth et al. introduced how UCEF leveraged the IEEE's High-Level Architecture (HLA) standard [15] for communication between multiple simulation federates. Singer et al. [16] developed a method to connect EnergyPlus with UCEF using a Functional Mock-up Unit (FMU).

In the simulation, five building simulators are implemented with a building energy management system, and a utility federate. Each building simulator represents a group of residential buildings (10 buildings) with the same model listed in Table 1. For each time step, the Building Simulator sends the time information and simulated metered energy consumption to the BEMS. Once the simulation scenario time reaches the beginning of an hour, the BEMS predicts the energy consumption of the current and next hours and sends them to the utility federate. By comparing with the grid capacity, the utility federate may propose a new price to the BEMS or directly publish the price as the cleared price. If a new price has been proposed, the BEMS adjusts the HVAC setpoint of each building based on users' price sensitivity and reports an updated energy consumption estimation to the utility federate. This negotiation process keeps going on until a cleared price has been published. The BEMS sends the final HVAC setpoint to building simulators based on the final price. The building simulators update the HVAC setpoint and proceed to the next timestep. The local weather is loaded by the building simulator. The detailed schematic graph is shown below in Fig. 3.

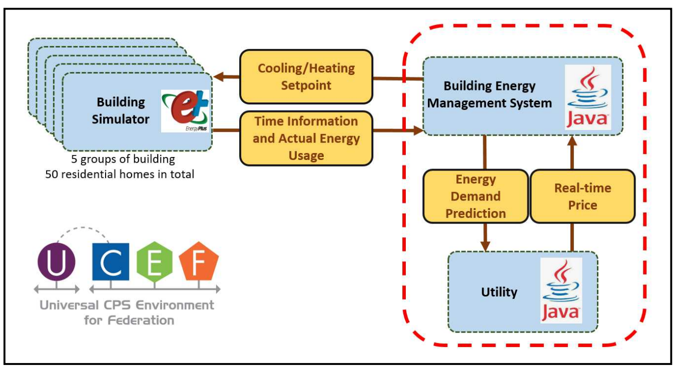

Fig. 2. Schematic diagram of data transfer between building simulator, building energy management system and utility

III. Experiment Setup

In this work, the HVAC energy demand of a small residential community is simulated, including five groups of buildings, and each group contained ten residential houses. The typical meteorological year (TMY3) weather file for Maryland is used [17]. Two simulations are run for seven-day periods: January 1 - 7 and September 6 - 10. The week in January is selected to test the performance of the pre-heating method in winter. The September week is selected to test the pre-cooling technology. The regular setpoints of HVAC system are 24 °C for cooling and 20 °C for heating. A fixed setpoints control strategy test (setpoints fixed at 24 °C and 20 °C) is also simulated as the baseline representing the most common user behavior.

The energy usage prediction function of BEMS is implemented by using a reference table. For each building model, eight tests are run with different 3-hour long pre-cooling strategies, which enumerated all the possible combinations. Table 2 lists the exact pre-cooling state of each hour in the eight tests. The binary value in Table 2 indicates whether the house used a pre-cooling strategy in one specific hour, corresponding to the time column. The results of the eight test runs are aggregated into one energy consumption reference table for each building model. The BEMS picks the corresponding energy consumption value from the reference table and reports it to the utilities. For example, if the building uses the regular setpoints from 9 AM to 10 AM and plans to use the pre-cooling setpoints from 10 AM to 12 PM, the BEMS will pick the energy consumption value from Test #3 as the prediction. A similar reference table is also generated for pre-heating strategy in winter. To validate this energy prediction method, two hours in a day are randomly selected as the pre-cooling/pre-heating period and simulated for the whole week. The result shows the average error of this prediction method is about 5 %.

TABLE II. PRE-COOLING STATE IN EIGHT TESTS

	Time (for both AM and PM)[a]											
Test	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
0	0	0	0	0	0	0	0	0	0	0	0	0
1	0	0	1	0	0	1	0	0	1	0	0	1
2	0	1	0	0	1	0	0	1	0	0	1	0
3	0	1	1	0	1	1	0	1	1	0	1	1
4	1	0	0	1	0	0	1	0	0	1	0	0
5	1	0	1	1	0	1	1	0	1	1	0	1
6	1	1	0	1	1	0	1	1	0	1	1	0
7	1	1	1	1	1	1	1	1	1	1	1	1

a. Time interval is an hour.

This work collects the data of day-ahead wholesale market price of energy from the California Independent System Operator (CAISO), which maintains the reliability of the California power system. Fig. 1 below demonstrates the actual retail and market price of energy in a week (Feb 12 - 18, 2021).

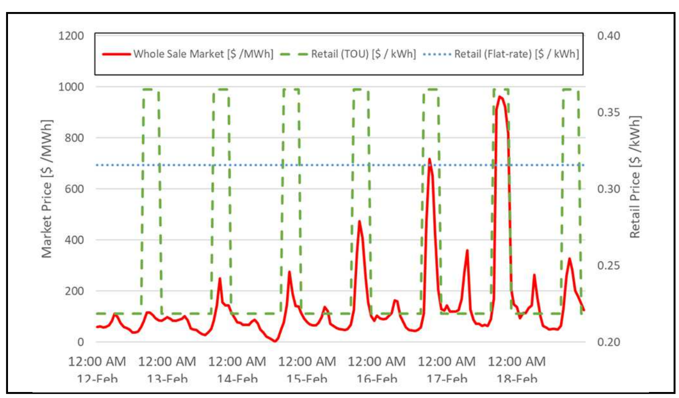

Fig. 3. Actual wholesale market and retail price of energy for February 12 – 18, 2021.

In Fig. 1, the maximum price ratio between two consecutive hours is approximately 8, happens 11 AM on 18th Feb. However, the price ratio in the retail market is just 1.7 for the TOU method and 1 for the flat-rate method.

The proposed pricing model sets $P_{default}$, P_{max}, P_{min}, ΔP, and $\Delta P'$ as \$0.32 /kWh, \$0.64 /kWh, \$0.08 /kWh, \$0.03 /kWh, and \$0.04 /kWh, respectively. As such, the maximum number of negotiation rounds is 8. And the most considerable price ratio (P_{max} /P_{min}) in the pricing model is 8, which matches the data presented in Fig. 1. The actual price ratio in the wholesale market can be as large as 20 during an emergency/critical peak period which cannot be reflected by this pricing method. This pricing model would be a good first step in making the customers aware of the cost of supplying energy.

IV. RESULTS AND DISCUSSION

Fig. 4 illustrates the simulation result of 5 hours long period, which contains a three-hour peak-usage period. 185 kWh was set as the threshold of E_c, which means it is a peak-usage hour when the total energy consumption greater than 185 kWh. The peak usage state stays three hours long from 5 - 8 AM with the fixed setpoint control. With the pre-heating strategy, a group of the buildings raise the setpoint from 4 AM. As such, the energy consumption increases from 4 - 5 AM and decreases from 5 - 8 AM. Just in this one design day, the peak load duration is reduced from 3 hours to 1 hour, and the actual peak demand is also decreased by 2 %, from 188 kWh to 184 kWh.

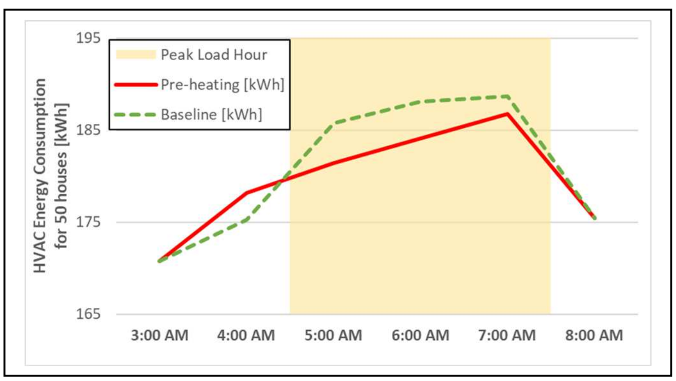

Fig. 4. Demonstration of the energy consumption in a winter day with a three hours long peak demand peroid.

A similar result has also been found in the cooling scenario in Fig. 5. Because the cooling load is much smaller than the heating load in Maryland, E_c is decreased to 50 kWh to show the performance of the TE scheme. Fig. 5 shows the energy consumption on a summer day. The peak usage duration is reduced from 6 hours (12 PM – 5 PM) to 4 hours (2 PM – 5 PM) by adopting the multi-round real-time pricing method and pre-cooling strategy. The actual peak consumption does not show a significant drop since it happens at the 4th hour in the peak load period. The load-shifting strategies used in this paper, pre-cooling and pre-heating, cannot impact the HVAC consumption after 2 hours.

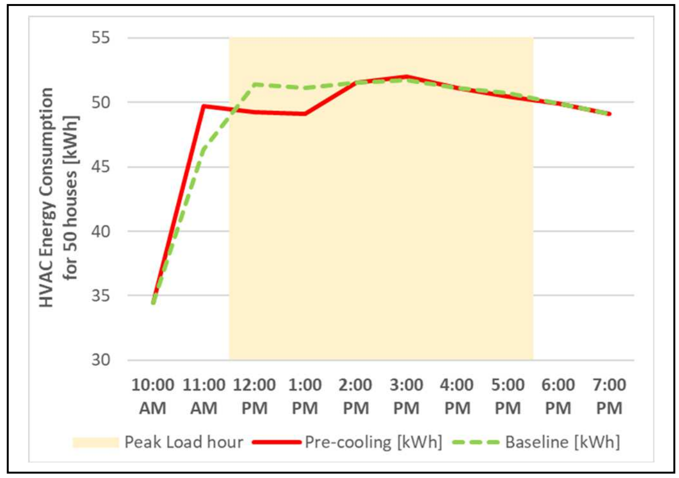

Fig. 5. Display the energy consumption in a summer day with a six hours long peak demand peroid.

During the simulated weeks, the hourly negotiations with more than one round only happened 1 to 2 times a day for each household, 22 in total for the simulation. The average number of negotiation rounds is 4.4, with a median of 4. Only two negotiations run eight rounds, reaching the P_{max} and P_{min}. The negotiation is seamless in the current experiment setup and may take longer in a larger simulation.

The total cost for the consumer was compared with the baseline model for both summer and winter time, as shown in Table 3. The overall weekly saving of the TE scheme and load-shifting behavior are \$ 1.22 in winter and \$ 0.25 in summer, with the difference between winter to summer due to a lower cooling load in the tested location. However, the saving ratio is about the same, around 1 %.

TABLE III. SUMMARY OF COST SAVING BETWEEN BASELINE AND PROPOSED PRICING MODEL WITH AND WITHOUT LOAD-SHIFTING BEHAVIOR

		Cost(\$)	Saving(\$)	Percent
Winter	Baseline	111.23	0.00	0 %
	Proposed model w/o load-shifting	111.33	-0.10	0 %
	Proposed model w/ load-shifting	110.01	1.22	1 %
Summer	Baseline	33.53	0.00	0 %
	Proposed model w/o load-shifting	33.78	-0.25	-1 %
	Proposed model w/ load-shifting	33.28	0.25	1 %

In Table 3, the winter results also show that for the customers who cannot or are unwilling to practice the pre-heating strategy almost don't need to pay extra money in the proposed pricing scheme. In the summer scenario, the additional cost of not practicing load shift rises to about 1 %. Because of the limited cooling load in the tested location, the HVAC system only needs to operate between 12pm to 5pm, which are the peak usage hours. These non-interactive customers cannot leverage the benefit of low price due to off-peak hours. This value would be reduced if we could include other electrical appliances which use more energy during the off-peak hour, such as an electric vehicle charger. In this manner, there would be no loss for the residential customers to join and adopt this multi-round real-time pricing scheme.

During the simulation periods, the duration of the peak usage hour for the week has been reduced from 19 to 12 hours in winter and 24 to 18 hours in summer. The maximum peak usage also decreased by 3 % in winter and 1 % in summer. This value seems slight compared with Maryland TOU pilots reduced peak load by 10% in summer and 5% in winter [3]. One reason is this simulation only considers the HVAC load. Including other easy-to-switch appliances (e.g., dishwasher, dryer, and EV charger) would help to improve the peak shaving impact. Another potential reason is this work uses a conservative load optimizer, which aims to always maintain the room temperature in the comfortable band. Instead of load-shifting, using a demand-response load-reduction optimizer would also enhance the peak shaving effect. The utilities will not benefit from charging more money from their users but from the reduction of peak usage which allows them to reduce the need for running and maintaining expensive peaking power plants [18].

Overall, the results show the potential saving impact of the multi-round real-time pricing method and load-shifting technology. This work calls for future work to develop the most efficient pricing models for TE. The simulation strategy is adaptable to incorporate additional considerations, such as commercial building models, different locations, and more advanced HVAC control algorithms.

V. Conclusion and Future Work

This work explores a co-simulation platform to demonstrate the peak shaving of a multi-round real-time pricing method in a TE scheme. A building energy management system has been devised and utilized to automatically engage in load-shifting behavior based on users' price sensitivity. Five groups of ten households were simulated to consider the variety of the buildings in a small community. A multi-round pricing model was developed and coded to publish an hourly energy rate that makes the retail prices track wholesale market prices. The results show that the proposed model can save 1 % of the cost in both summer and winter time for the customer adopting a load-shifting strategy. The utilities are also benefiting from the reduction of the actual amount and duration of the peak-usage period.

The validation method explored in this work is highly adaptable for different control algorithms, energy prediction models, pricing models, building models, locations, and weather conditions. Each simulation entity can be tested independently so that other studies can readily adopt this work for testing and validation.

The HVAC is not the only energy usage in the building. With the development of IoT technology, more and more appliances are able to communicate and be controlled remotely. The operation of these appliances can be easily shifted to an off-peak demand period, such as dishwasher, washer, and dryer. By implementing a more sophisticated price-based control algorithm in the BEMS, the whole TE system should communicate not only to the HVAC system but also to all appliances in the building. Another direction for future work is developing a new load prediction model, allowing BEMS to predict and report the energy demand in the next hour. The utilities would be able to estimate the time and magnitude of the demand peak more precisely. The actual peak demand reduction potential of TE could be measured via this co-simulation platform.

Acknowledgment

This work was completed in the NIST Communications Technology Laboratory– as part of the IoT Devices and Infrastructures Group. Official contribution of the National Institute of Standards and Technology; not subject to copyright in the United States. Certain commercial products are identified in this paper to foster understanding. Such identification does not imply recommendation or endorsement by the NIST, nor does it imply that the products identified are necessarily the best available for the purpose.

References

[1] Holmberg, David, et al. "NIST Transactive EnergyModeling and Simulation Challenge Phase II Final Report." NIST special publication (2019).

[2] American Public Power Association, "Moving Ahead with time of Use Rates", https://www.publicpower.org/system/files/documents/Moving-Ahead-Time-of-Use-Rates.pdf, April 2022.

[3] The Brattle Group, "Study by Brattle Economists Evaluates Time-of-Use (TOU) Pilots for maryland Utilities, https://www.brattle.com/insights-events/publications/study-by-brattle-economists-evaluates-time-of-use-tou-pilots-for-maryland-utilities/, April 2022.

[4] Pacific Gas and Electric Company, "Electric Schedule EM-TOU Residential Time of Use Service", https://www.pge.com/tariffs/assets/pdf/tariffbook/ELEC_SCHEDS_E-6.pdf, April 2022

[5] The Brattle Group, "A Survey of Residential Time-Of-Use (TOU) Rates, https://www.brattle.com/wp-content/uploads/2021/05/17904_a_survey_of_residential_time-of-use_tou_rates.pdf, April 2022

[6] Zethmayr, Jeff, and David Kolata. "The costs and benefits of real-time pricing: An empirical investigation into consumer bills using hourly energy data and prices." The Electricity Journal 31.2 (2018): 50-57.

[7] Widergren, Steve, et al. "Residential transactive control demonstration." ISGT 2014. IEEE, 2014.

[8] Burns, Martin, et al. "Universal CPS environment for federation (UCEF)." 2018 Winter Simulation Innovation Workshop. 2018.

[9] Crawley, Drury B., et al. "Energy plus: energy simulation program." ASHRAE journal 42.4 (2000): 49-56.

[10] Price, Phillip N., et al. "Automated Measurement and Verification of Transactive Energy Systems, Load Shape Analysis, and Consumer Engagement." (2014).

[11] Residential Prototype Building Models, U.S Department of Energy Building Energy Codes Program, https://www.energycodes.gov/development/residential/iecc_models, Feb 2022.

[12] Uddin, Moslem, et al. "A review on peak load shaving strategies." Renewable and Sustainable Energy Reviews 82 (2018): 3323-3332.

[13] Xu, Peng, et al. Peak demand reduction from pre-cooling with zone temperature reset in an office building. No. LBNL-55800. Lawrence Berkeley National Lab.(LBNL), Berkeley, CA (United States), 2004.

[14] American Society of Heating, Refrigerating and Air-Conditioning Engineers, "Standard 55 – Thermal Environmental Conditions for Human Occupancy",https://www.ashrae.org/technical-resources/bookstore/standard-55-thermal-environmental-conditions-for-human-occupancy, April 2022

[15] Roth, Thomas, et al. "Cyber-physical system development environment for energy applications." Energy Sustainability. Vol. 57595. American Society of Mechanical Engineers, 2017.

[16] Singer, Joe, et al. "EnergyPlus integration into cosimulation environment to improve home energy saving through Cyber-Physical systems development." Journal of Energy Resources Technology 141.6 (2019).

[17] Weather Data by Location, Baltimore-Washington Intl AP 724060 (TMY3), https://energyplus.net/weather-location/north_and_central_america_wmo_region_4/USA/MD/USA_MD_Baltimore-Washington.Intl.AP.724060_TMY3, Feb 2022.

[18] Faruqui, Ahmad, et al. "The power of 5 percent." The Electricity Journal 20.8 (2007): 68-77.