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Prevision and planning for residential agents in a transactive energy environment

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ABSTRACT

Transactive Energy (TE) has brought exciting opportunities for all stakeholders in energy markets by enabling management decentralization. This new paradigm empowers demand-side agents to play a more active role through coordinating, cooperating, and negotiating with other agents. Nevertheless, most of these agents are not used to process market signals and develop optimal strategies, especially in the residential sector. Accordingly, it is indispensable to create tools that automate and facilitate demand-side participation in TE systems. This paper presents a new methodology for residential automated agents to perform two key tasks: prevision and planning. Specifically, the proposed method is applied to a forward market where agents' planning is a fundamental step to maintain the dynamic balance between demand and generation. Since planning depends on future demand, agents' prevision of consumption is an inevitable part of this step. The procedures for automating the targeted tasks are developed in a general way for residential prosumers and consumers, interacting at the distribution level. These players are managed by a demand aggregator as the leader by means of the Stackelberg game. The suggested process results in a TE setup for multi-stage single-side auctions, useful to manage future Smart Energy Markets. Through simulated transactions, this paper examines the market clearing mechanism and the convenience of agents' planning. The results show that customers with higher price-elasticity leverage lower costs periods. However, they make it harder to reduce the peak-to-average ratio of the aggregated demand profile since a unique price signal can create prisoner's dilemma conditions.

1. Introduction

Energy systems must confront significant challenges to successfully integrate renewable resources due to their intermittency and variability [1]. Accordingly, several technologies have been deployed to realize smart energy systems that offer more flexibility and sustainability. The new technologies allow for identifying synergies between electricity, thermal, and gas grids regarding optimal global solutions [2]. These advancements along with new energy market designs can exploit the potential of each component in the system. Diverse innovative market solutions using smart infrastructure can result in a better resource allocation to improve security, equity, and social welfare [3].

Some of the most promising market designs in electrical grids are based on Transactive Energy (TE) [4]. The main objective of TE is to decentralize grid management in order to help stakeholders maintain the balance of the grid while pursuing their objectives. The change from centralized to decentralized optimization improves grid management because it reduces uncertainties, risks, and inefficiencies [5]. Particularly, the changes in electricity markets affect all energy sectors due to the conversion stage, needed for the final energy use and the synergy with other energy grids.

The TE paradigm applied to energy markets transforms all

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stakeholders into decision-makers that interact (coordinate, cooperate, and negotiate) with each other [6]. In this sense, TE creates complications for stakeholders that have a passive role like residential customers. Indeed, these customers have to process a significant amount of data to quickly develop a consumption strategy and find resources through the whole smart infrastructure [7]. This situation necessitates employing automated tools to fulfill the transactions on behalf of the residential customers [8]. In this paper, the automated device is referred to as an agent.

In the literature, the feasibility of integrating residential agents into grid management has been studied by the game theory [9]. Indeed, different enhancements have been made towards a framework for agents' interactions in distribution grids [10]. However, residential agents' rationality has been assumed without special considerations to how they create beliefs, update their desires, and generate intentions. Therefore, it is necessary to define agents' behaviors in detail and develop standard procedures for their tasks. The development of reliable agents help engage customers into TE systems [11].

Since grid management depends on agents' interactions and agreements, the information that they share is one of the most important aspects to control [12]. There should not exist incentives to lie in a well-designed mechanism, and each decision-maker must minimize information errors [13]. For instance, residential agents need to have a comprehensive understanding of their energy consumption and retailers need to supply accurate price signals. In this scenario, residential agents must perform some anticipation tasks to ensure that their information is reliable. They need a prevision of uncontrollable variables and a plan to handle controllable loads. This anticipation helps build trust and define other agents' behaviors like local control.

In the specific case of forward-markets, the agents' anticipation tasks define the operation of the grid [14]. In such context, agents agree on energy price and consumption for future delivery, and then they execute their plans to fulfill agreements and avoid penalties. Table 1 summarizes different authors' proposals for agents' interaction to reach agreements, explicitly in electric grids. Most of the literature approaches do not take into account agents' information needs from diverse sources such as weather data or user' valuations. Besides, some interaction schemes do not consider the extend of the solutions considering large TE systems. For these scalability issues, a demand aggregator agent is favored as a great bridge to link residential agents and wholesale energy markets [15].

In this paper, the proposed market configuration is a Stackelberg game where the aggregator leads the interaction to realize a forward contract with the residential agents as followers. Consequently, each residential agent formulates its strategy based on the signals it receives without either parametrizing or anticipating other agents' responses [25]. The observability conditions of agents are different. Residential and aggregator agents fail to parametrize market signals and individual consumption, respectively [26]. As a result, they both have to trust the information they receive [27]. TE mechanisms are beneficial for building such trust since they are multistage games that allow agents to discover information while they interact [16]. Thus, in the end of the interactions, agents will not have an incentive to deviate from their plan considering other agents' strategy. This condition leads to a Nash equilibrium point [28].

The residential agents' strategy is formulated to maximize the utility by balancing costs and customers' comfort considering the constraints of loads dynamics [29]. Energy conversion technologies in smart energy systems (like power-to-X) are advantageous because they allow formulating strategies without excessively compromising comfort [30]. Indeed, residential agents can characterize all their behind-the-meter resources (local environment) and make an integrated consumption plan. This characterization of the local environment can be done by using data-driven and stochastic modeling approaches [31]. Besides, an agent can adapt these models to overcome the accuracy loss when external conditions change [32]. In this case, for simplicity in data management, energy consumption and generation devices are considered in groups.

Once the residential agent has characterized its local environment, it can make a prevision and process the market signals to optimize its energy consumption plan. Afterwards, it can communicate its plans and intentions with the demand aggregator or other participants in the Multi-Agent System (MAS). To complete this procedure and systematically integrate the prevision results into the planning procedure, it is valuable to have a structured software design in terms of agent-oriented programming. Such scheme can also contribute to the scalability of TE solutions [33]. Within this context, this paper aims to promote standard procedures for the prevision and planning tasks of residential agents in a TE system. The contributions of this work can be summarized as follows:

Table 1
Limitations in state of the art work.

Interaction scheme	Achievements	Limitations
Cournot competition [16]	Considers customers' willingness to pay and preferences.	Agents interact directly in the wholesale market, making it problematic for large power systems.
Coordination of opportunistic agents [17]	Optimal scheduling of appliances according to resource availability. Impose agents' solutions over customer preferences.	Increase the implementation requirements since it proposes a MAS in the local environment.
Distributed demand response algorithms [18]	Improved (flatten) aggregated demand profile.	Agents need to be informed about their peers' strategies and the pricing scheme.
Centralized demand response with TE as security mechanism [19]	Combined approach to overcome imbalances in the grid and improve system resiliency.	Agents depend on centralized optimization and forecasts.
Peer-to-peer trading [20,21]	Proved economic benefits for the agents.	Assumes perfect information and perfect agents that make rational decisions
Coalition operations and collaborative agents [6,22]	Interactions between agents successfully integrate DER and bring economic benefits. Scalable solutions.	Coalitions among suppliers left customers in a disadvantageous position.
Double-side auctions [7,23]	Independent agent strategies. Information privacy. Improved cost allocation.	Lower social welfare compared with iterative games.
Aggregators' direct load control [24]	Reduces uncertainties.	It does not consider customers' preferences and information privacy.
Stackelberg game with MAS in the local environment [25]	Economic benefits for the residential agent.	Hard to extend for multiple agents since retailers have to send in advance a definitive price signal without information about the consumption.
Energy Hubs [9]	Distributed grid management. Scalable solution.	Assumes deterministic consumption with perfect agents.

- A sequential interaction protocol between residential agents and a demand aggregator agent to find equilibrium points in an iterative Stackelberg game. As a result of this interaction, the agents reach forward contracts that set the energy price. Moreover, this protocol allows the aggregator to coordinate the demand in a small part of an energy system and offer useful insights for managing the wholesale energy market.
- A planning algorithm based on agent-oriented programming paradigm for solving residential agents' information needs in TE. The algorithm is used to find the best consumption strategy according to the perception of local environments and the price signal. This helps characterize the agents' rationality that is commonly assumed in the literature. Agents' behavior is formulated for groups of appliances considering risk-neutral users in order to overcome customers' heterogeneity.

By explicitly defining the decision-making procedure of residential agents, this work addresses the problem of assuming perfect agents with perfect information that is common in the literature, as presented in Table 1. Furthermore, it proposes to manage energy systems by coordinating the demand of small parts through aggregator agents owing to forward-markets potentials. These aggregators have proven to bring benefits to all stakeholders in the system [15]. Through this proposition, we prevent residential agents from interacting directly with wholesale markets since it complicates the management of large energy systems.

The rest of this paper is organized as follows: Section 2 explains the developed framework of TE and the opportunities of residential agents in the market. Section 3 presents the proposed procedures for residential agents to perform the anticipation tasks with the definition of their behaviors. The experimental setup and results, obtained from case studies with simulated transactions, are discussed in Section 4, followed by the concluding remarks in Section 5.

2. Transactive energy framework

Transactive Energy systems are composed of economic and control mechanisms that allow the dynamic balance of supply and demand by using value as a key operational parameter [34]. The main features that differentiate TE from other grid management schemes are the distributed decision-making process and the two-way communication channel between all agents [35]. TE allows agents interaction to find equilibrium points and balance the grid. Particularly, user-perceived values reflect their willingness to pay. In an aggregated manner, these valuations tune the price of energy and services in the transactions [36].

Commonly, interactions between agents are not unique because they can have different objectives. For example, retailers and final consumers can have opposite objectives and thus, they should negotiate. On the other hand, two prosumers with similar objectives can cooperate [37]. Individually, each agent looks for optimizing its payoff function. However, at the end, the system reaches an equilibrium with agreed transactions [38]. Normally, agents have to know market rules and perhaps even pricing schemes and taxation regulations before agreeing on transactions [39].

In this study, we consider that agents representing residential customers interact only with a demand aggregator. Therefore, residential prosumer and consumer agents negotiate with this aggregator agent to buy or sell energy in a forward market [40]. For simplicity, it is assumed that the only commodity in trades is active energy. It should be noted that TE is conceived for electricity grids and its implementation requires all the layers, proposed in the Smart-Grid Architecture Model (SGAM), to provide communication between agents [41]. The schematic of the proposed setup is presented in Fig. 1, where HQ is the aggregator agent and H1, H2, …, Hk are the residential agents. Since the system is not meant to operate as an isolated microgrid, generation resources adequacy and reliability are not advised [42].

Since there is only one commodity in trades, the exchanged messages between the agents are more straightforward than others proposed in the industry such as OpenADR and ANSI/CTA 2045 [43]. Firstly, the aggregator registers the residential agents. Afterwards, it waits for the “ready” (RDY) message from each one to start the interaction process. All agents have to participate in all market periods even if they send void purchasing or selling offers. When all agents are ready, the aggregator, as the leader, sends the price signal first and then, waits for each residential agent's response. Finally, whenever the aggregated demand profile is satisfactory, the aggregator sends an “acknowledgment” (ACK) message and the residential agents assume their last proposed consumption is accepted. This interaction is represented by the Unified Modeling Language (AUML) in Fig. 2.

It is presumed that there are no security concerns in lower layers since the interaction is made on high-level communication layers by utilizing protocols like XMPP or MQTT [44]. The main advantage of the strategy of waiting for each response is that it ensures all residential agents participate in transactions even if it takes longer processing times than other approaches in the literature [40]. Since the residential agents get a forward contract, their planning and interaction procedures are made in advance and consequently, the processing time is not critical.

The changes in the residential sector strategy towards transacting active energy inevitably affect other energy markets [45]. Moreover, residences can be directly connected to heat and gas grids in order to supply specific demands by switching the technologies [46]. Accordingly, it is necessary to analyze the scaling options of a market re-design to advise a higher social welfare [47]. In this regard, the proposed agents' interaction allows for coordinating the residential sector active energy demand, in advance, and using the resulting forward contracts for clearing the wholesale electricity market. Furthermore, the results can be utilized in other energy markets to forecast the demand.

2.1. Proposed aggregator agent architecture

In the value discovery mechanism, the aggregator, as the leader of a Stackelberg game, makes an initial assumption about residential agents' consumption to start negotiations [25]. Under this concern, the proposed agent architecture for aggregators has four behaviors, as presented in Fig. 3. First, the aggregator agent gets data from two components of the price accounting for the unitary cost of energy and the initial incentive or commercialization/aggregation rate. Second, it registers customers and perchance classifies them according to their demand flexibility or elasticity. Third, it takes the residential agents' responses to update the demand model and formulate the pricing strategy based on an optimization problem. The pricing strategy corresponds to the aggregator's

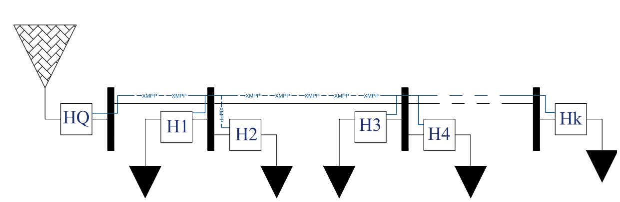


Fig. 1. System setup with one demand aggregator.

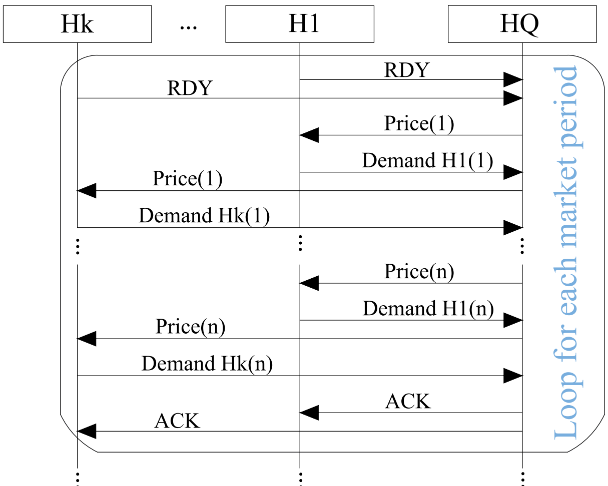


Fig. 2. Proposed AUML diagram.

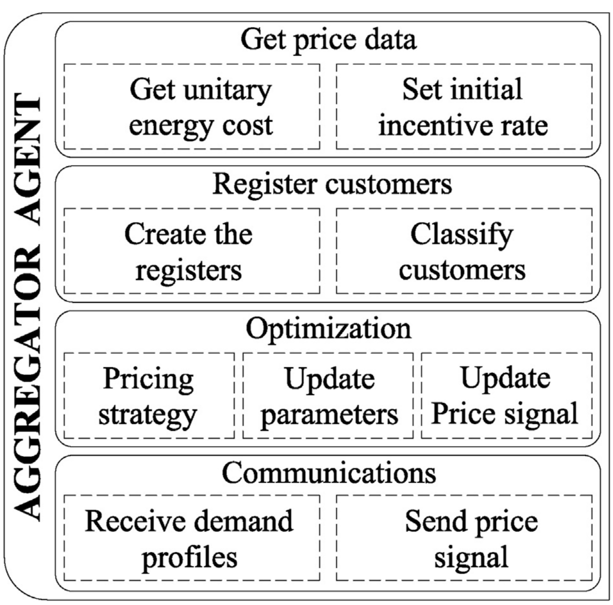


Fig. 3. Aggregator Agent architecture.

objective in the energy system. Generally, in electrical grids, the aggregator's goal is to flatten the aggregated demand profile minimizing the peak-to-average ratio (PAR) [48]. It should be noticed that it is possible to minimize the PAR by employing reinforcement learning techniques without building the demand model [49]. Finally, the aggregator agent architecture requires a behavior to communicate the price signals with the residential agents.

Employing a single aggregator to minimize PAR improves risk management and grid assets use [42,50]. However, it is interesting to have competing aggregators in order to mitigate their market power in cases where they try to maximize revenues [15]. The problem formulation for the aggregator in our case is presented in Eq. (1).

$$\min_{I_1,\ldots,I_T} PAR = \frac{T \max(P_1,\ldots,P_T)}{\sum_{t=1}^{T} P_t} \tag{1}$$

$$st : P_t = P_{flex,t}\pi_t + P_{fix,t} \quad \forall t \tag{2}$$

$$\pi_t = UC + I_t \tag{3}$$

$$\sum_{t=1}^{T} P_t I_t = E \tag{4}$$

Where, I_t (decision variable) stands for the incentives at each time t, and P_t is the power demand signal discretized in T energy blocks according to the market period. UC stands for the unitary cost of electricity and E expresses the expected revenue. Normally, the price π_t is the sum of UC and I_t. Here, UC is considered as a constant value that the aggregator knows beforehand from the wholesale market. Since a part of the electricity demand is inelastic (even some appliances can be necessity goods), E has a limit, given by a revenue cap regulation. The optimization horizon, T, is often set to 24 h (day-ahead) in forward-markets. However, reducing T can be suitable for micro-grids because it can assist with a reliable forecast of intermittent distributed energy resources (DER) [51].

The aggregated demand, P_t, is modeled as a linear function of the price as naive approach without further information on each house appliances. $P_{fix,t}$ and $P_{flex,t}$ correspond to the fixed and proportional parts of the demand, respectively. These parameters are estimated from a simple linear regression by using the Least-squares method based on Eqs. (5) and (6) with normally distributed error term (as an assumption). An individual incentive formulation for each customer by using independent values of $P_{fix,t}$ and $P_{flex,t}$ can result in a lower PAR considering users' participation in various energy markets. However, this is out of the scope of this paper. Besides, when there are only consumers and the energy price is ensured to be positive, the demand can be modeled as a function of the logarithm of the price to accelerate the convergence.

$$\widehat{P}_{flex,t} = \frac{COV(\pi_t, P_t)}{VAR(\pi_t)} \tag{5}$$

$$\widehat{P}_{fix,t} = \overline{P_t} - \widehat{P}_{flex,t}\overline{\pi_t} \tag{6}$$

The mean values, $\overline{P_t}$ and $\overline{\pi_t}$ are incrementally updated in each iteration of the negotiation process. Similarly, the variance, (VAR) and covariance, (COV) are updated with the Welford's online algorithm [52]. The iterative process between the aggregator and the residential agents stops when there are no significant changes in the estimated regression parameters.

3. Residential decision-making process

The Pacific Northwest National Laboratory (PNNL) summarizes the tasks that stakeholders should perform to participate in TE systems as follows: planning, prevision, local control, register, negotiation, check-out, and reconcile [35]. Indeed, the success of these tasks depends on the knowledge that the agent has about its environment. In the residential agent context, we can distinguish two environments that account for a local environment composed

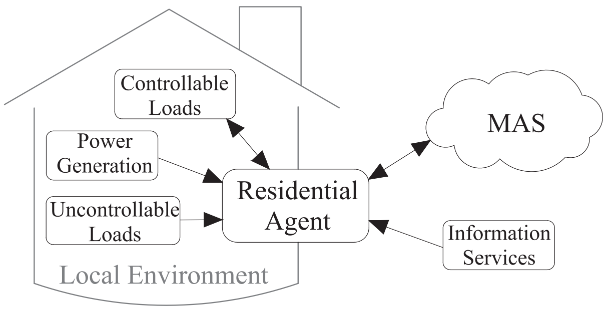


Fig. 4. Interaction of the residential agent with its environments.

of behind-the-meter resources and a transactive environment as the MAS. Fig. 4 presents the interactions of the residential agent and its environments. Due to the number and heterogeneity of appliances that a house can have, it is convenient to classify them into controllable loads, uncontrollable loads, and power generation devices.

Automating the tasks for residential users is essential because the flexibility in this sector comes from elastic users operating controllable loads. However, exploiting flexibility can be challenging if users do not appropriately respond to market signals. Instead, an automated agent guarantees rationality in the operation of loads at least inside the range of its observability [53]. The residential sector flexibility assists with the proper incorporation of intermittent and variable renewable resources, which, in turn, results in more sustainable energy systems.

This work focuses on the planning and prevision tasks because they define the operation of a forward-market. The planning intends to find the right sequence of actions to minimize cost considering the agents' Beliefs, Desires, and Intentions (BDI) [54]. The BDI approach implies that the residential agent has reactive behavior to respond to events and cognitive behavior to model its environment. Note that, in this context, agent's behavior defines activities that should be performed autonomously without external instruction [55]. In brief, the residential agent acquires the following.

- Beliefs corresponding to models that are built by using the local environment.
- Desires that are expressed in the pay-off function of an optimization problem.
- Intentions that present the solutions to the optimization problem during the planning task.

Since weather conditions influence both power generation of DER and energy consumption, the residential agent needs to receive weather data from an external information services to plan its strategy. Therefore, the first step in the anticipation tasks is to connect to those information services. It should be noted that the agent carries out the consumption planning in a way to reach a forward contract. Therefore, it should trust the weather forecast to formulate its action [56]. The next step in the planning procedure is to get data related to user's price-elasticity. This information can be obtained directly from a Human-Machine Interface (HMI) or inferred by using preference learning methods. Once the agent has both weather forecasts and price-elasticity data, it is ready to receive price offers and solve its optimization problem. The proposed planning procedure is summarized in the Algorithm 1.

Algorithm 1. Residential agent planning procedure.

Algorithm 1: Residential agent planning procedure

inputs : Historical data of consumption and its explanatory variables (environmental conditions)
output: Energy consumption strategy
begin
    Get weather forecast for the next market period;
    Get user's price-elasticity;
    Adapt the models of appliances if needed;
    Make the prevision of uncontrollable consumption:
        Forecast the fixed load consumption;
        Forecast the power generation ;
    Receive price offers for the next market period ;
    Optimize to find the consumption strategy for controllable loads;
    Send the expected total consumption for the market period;
end

In the Stackelberg game configuration, presented above, the residential agents are followers and thus, they wait for the aggregator's offers. Since there is only one aggregator, the residential agents do not need to arrange bids and they can recognize the market period directly from the price signal [5]. The follower agents formulate their best strategy, s^*, by taking into account only the price signal, which they receive at each moment. It is noted that the complexity of the MAS and the unobservability of other agents' responses make it infeasible to parametrize the price signal [57]. Therefore, residential agents undergo difficulties to find perfect subgame equilibrium points albeit knowing that the TE mechanism has an optimal substructure [24]. This limitation can be regarded as a major issue of spot markets (not forward-markets) due to their small planning window.

The consumption strategy, s^*, deals with controllable loads, $P_{cl,t}$, uncontrollable loads, $P_{f,t}$, and power generation devices, $P_{g,t}$. The models of uncontrollable loads and power generation devices are required to forecast their outcomes. On the other side, the model of controllable loads is needed to know their dynamics under different conditions and evaluate the strategies' feasibility. As a result, the total estimated consumption, $\widehat{P}_t$, for a given time, t, can be computed by Eq. (7).

$$\widehat{P}_t = \widehat{P}_{f,t} + P_{cl,t} - \widehat{P}_{g,t} \tag{7}$$

Accordingly, the architecture to accomplish the prevision and planning tasks is presented in Fig. 5. It contains six asynchronous behaviors with no hierarchical order comprising data acquisition, adaptive modeling, optimization, local control, reconciliations, and communications. The agent's primary knowledge must contain the data window for training each model and all the external information, needed to solve the optimization problem. The calculation of reconciliations is also presented in the agent's architecture because the historical results of penalties can provide useful information for some users' planning. For instance, risk-averse agents can use past reconciliation costs to improve their strategies regarding asymmetric market penalties [23]. However, that is not part of the anticipation tasks considered here to be automated.

3.1. Data acquisition

The agent measures appliances' power consumption in the local environment and creates a data stream [58]. It can be convenient to

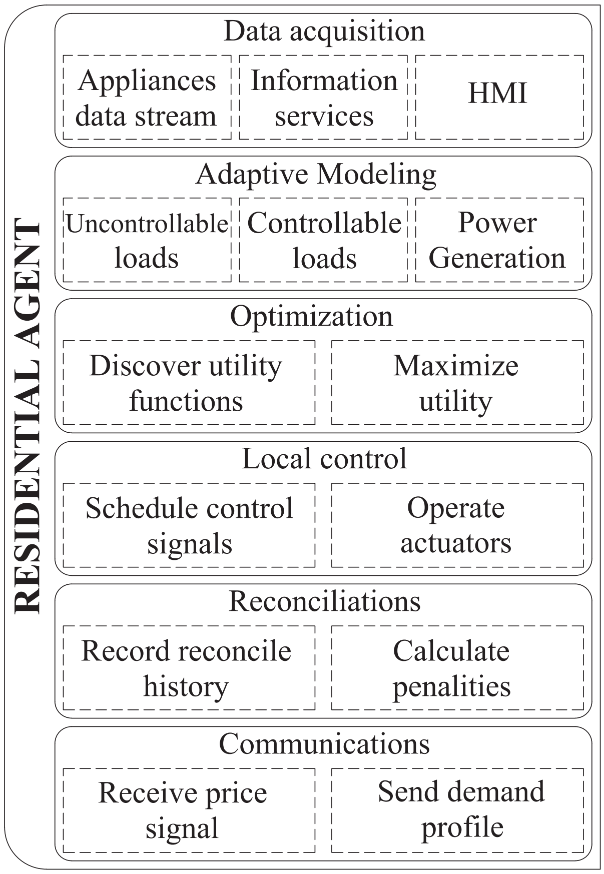


Fig. 5. Residential Agent's architecture.

implement lambda-based processing architectures for this behavior, depending on the sampling time and the number of appliances [59]. Consequently, the agent stores parts of the data stream, needed to create its environment models, in a time-indexed database. Furthermore, this database contains data from other sources such as weather forecast services to complete the information, required for the modeling phase.

Since the agent represents a final consumer, it is crucial to consider users' comfort constraints and price-elasticity. For this purpose, the data acquisition behavior includes an HMI that enables the communication between the agent and the user. For example, users could define preferred temperature setpoints for controlling heating systems, or state of charge limits for controlling electric vehicles [22,60].

3.2. Adaptive modeling

It is relevant to have an adaptive learning process because there can be concept drifts in the data. Concept drift is a change in the hidden joint probability between the consumption $(P_{f,t}, P_{cl,t}, P_{g,t})$ and its explanatory variables. In fact, the collected data can present any kind of drift because there are many changing sources. For example, weather conditions and appliances degradation can cause gradual drifts while technology upgrades can bring about sudden drifts. Therefore, the models should be adapted to overcome both kinds of drifts. This can be achieved by a suitable technique that is chosen considering the data management and the forgetting mechanisms as key factors. Models management or learning strategy can be adjusted according to the chosen configuration because not all the models can be ensembled or incrementally trained [61].

For the residential agent, a technique based on Fish and Drift Detection methods, presented in Ref. [62], is utilized. This manner, summarized in the Algorithm 2, is suitable for this case because it forgets less data and, in turn, allows the agent to train many models with a single data window.

Algorithm 2. Adaptive Learning method.

```
Algorithm 2: Adaptive Learning method
 inputs : Historical consumption data and weather
          forecast for the planning horizon
 output: Trained models
 begin
    Divide the historical data into sub-windows;
    Calculate the distance between each sub-window
      and the weather forecast;
    Make cross-validation using the closest sub-window
      as the test set and the rest of the data as training set;
    if Results have an acceptable error level then
       Train the model with all the available data;
       Forget old data only if there is no memory space;
    else
       Train the model with the closest sub-windows;
       Forget old data until the oldest selected
         sub-window;
    end
 end
```

It can be noticed that the algorithm depends on the distance between data sub-windows and the error metrics. Indeed, the distance in time in the data stream and the distance in feature space must be weighted. The euclidean distance is frequently used in the literature for measuring distance in feature space due to its fast calculation [63]. Afterwards, it is convenient to use relative metrics like the Normalized Root Mean Square Error (NRMSE) in the cross-validation step to make the acceptance criteria independent of the variable magnitude. The number of data sub-windows, selected to train the models, should be always enough to ensure convergence in training.

3.3. Optimization

Subsequently, the agent takes the prevision results from the local environment models to plan its consumption strategy. As a follower, the MAS is not fully observable because other agents' actions are not deterministic and exogenous events affect their strategies. Under these circumstances, it is unfeasible for the residential agent to parametrize the MAS. Alternatively, its best option is to trust the price signals that it receives. Under this choice, the agent's consumption plan is done with certainty and the only decision variable is the energy demand of the controllable loads. Such consumption strategy can be favored as the best action according to all the available information [27]. It should be pointed out that the prevision tasks of modeling and data acquirement should be carried out once per market period. Nevertheless, the planning problem must be solved at each iteration of the negotiation process.

The optimization problem for the residential agent is formulated in Eq. (8). The objective is to maximize the individual welfare as the difference between the utility, U_t, that the user perceives from consuming energy, and the cost, C_t, that it has to pay in return. The utility from uncontrollable loads does not shift the solutions, and thus U_t is a function of only $P_{cl,t}$. The cost function is a piecewise affine function depending on whether the agent is buying or selling energy. Usually, the buying price, π_t, is higher than the selling price,

λ_t, to remunerate the grid usage [64]. Finally, the aggregator can only send π_t, and λ_t can be settled as a constant percentage of that. This problem is constrained by comfort restrictions and dynamics of controllable loads.

$$\max_{\widehat{P}_1,\ldots,\widehat{P}_T} \sum_{t=1}^{T} U_t - C_t \tag{8}$$

$$C_t = \begin{cases} \pi_t \widehat{P}_t & \text{if } \widehat{P}_{g,t} \le \widehat{P}_{f,t} + P_{cl,t} \\ -\lambda_t \widehat{P}_t & \text{if } \widehat{P}_{g,t} > \widehat{P_{f,t}} + P_{cl,t} \end{cases} \tag{9}$$

The utility function depends on the controllable load and it must be concave. Furthermore, the utility function can be a function of either $P_{cl,t}$ or derived variables. For instance, U_t can be represented as a function of household internal temperature or the state of charge of batteries when controlling heating systems or electric vehicles, respectively. In the problem formulation, the significance of the utility function in comparison with the cost, C_t, reflects the user's price-elasticity. Therefore, the utility function often has a scale parameter that is tuned according to the user's preferences.

3.4. Local control

The local control of loads is not relevant to the anticipation tasks, but it can be usefully included in the agent's software architecture. In this behavior, the agent communicates with the drivers of controllable loads to follow the TE agreements. For this purpose, agents can integrate other models to adjust control actions with short-term forecast like time-series models of low computational cost [65]. Besides, this behavior can be expanded by other protocols to communicate with appliances.

3.5. Reconciliations

The estimated $\widehat{P}_{f,t}$ and $\widehat{P}_{g,t}$ can have errors due to the weather forecast and inner model inaccuracies. This results in deviations even if controllable loads are adjusted to follow exactly the TE agreement. Normally, energy contracts specify penalties for these kinds of deviations and involving regulations [66]. The reconciliation cost can be obtained right after the market period ends.

In power systems, some grid codes show that stability limits are not symmetric and thus, underestimating energy consumption can be cheaper than overestimating it for the grid operator. This effect can be translated to final consumers with different penalties for positive and negative deviations [67]. In this case, risk-averse agents can use previous reconciliation results to shift their consumption strategy and avoid higher penalties. However, this analysis considers risk-neutral agents whose best strategy is to communicate their estimates, $\widehat{P}_t$.

3.6. Communications

Finally, the residential agent needs a communication block to interact with other agents. It receives price signals and answers with the consumption strategy. The agent certainly needs to know the communication protocols, executed in lower levels of the smart grid. The schematic of the communications of the described MAS is presented in Fig. 6. The aggregator agent receives information from other higher-level agents or a market database (market DB) and communicates with the residential agents through a local server. The house DB represents the residential agents' primary knowledge.

4. Case studies

The implemented communication server uses the XMPP protocol to test the proposed TE configuration. The market period is 24 h. Energy and price signals are discretized in intervals of 5 min. The agents' behavior is programmed by using SPADE in python to make them asynchronous [68], and the optimization problems are addressed by using the solvers of SciPy [69].

For the residential agents, the utilized weather data corresponds to the conditions from 1st to February 5, 2018 in Trois-Rivières, QC. Regarding the residential agents' designs, the power generation is modeled by a feed-forward neural network with 100 neurons in five layers and a hyperbolic tangent as the activation function. The inputs of this model are the time of day, solar irradiance, wind speed, wind direction, cloud coverage, and external temperature. Besides, in order to forecast the consumption of uncontrollable loads, a Support Vector Machine (SVM) is used with a radial basis function as the kernel. In this case, the explanatory variables are a cosine signal with a 24 h period, the number of the days of the week (from 1 to 7), the external temperature, and the previous time interval consumption. In addition, the controllable load corresponds to a single-zone space heater. The dynamics of this load are modeled based on a linear function of its consumption, $P_{cl,t}$, and the external temperature, $\theta_{ext,t}$, as presented in Eq. (10). This model assumes that the current value of internal temperature, $\theta_{int,t}$, is linked to its previous one, $\theta_{int,t-1}$ [70]. The parameters α and β are obtained by the ordinary least-squares method and adapted through Algorithm 2 as the other models.

$$\widehat{\theta}_{int,t} = \alpha\theta_{ext,t} + (1-\alpha)\theta_{int,t-1} + \beta P_{cl,t} \tag{10}$$

For this controllable load, the utility function is presented in Eq. (11). θ_{ref} is the internal temperature that maximizes the customer's comfort and obtained from the thermostat set-points. This utility function is concave because there are no monotone preferences for temperature. In other words, the utility is non-decreasing while the marginal benefit is non-increasing. It should be noted that zero consumption does not imply zero utility in this case [71]. The parameter δ represents the user's elasticity and is considered constant. It is used for weighting the utility with respect to the cost. Since the only heating source is electricity, the utility function does not consider cross-elasticity with other resources. When the agent is participating in more energy markets, it is necessary to expand the utility and cost terms to find an optimal integrated strategy for consumption [47].

$$U_t = -\delta\left(\widehat{\theta}_{int,t} - \theta_{ref}\right)^2 \tag{11}$$

The electrical heating system as controllable load adds two new constraints to the agents' planning problem. First, the consumption, $P_{cl,t}$, cannot exceed the technical limit of the space heater. Second, the final internal temperature must be equal to the initial one in order to start every market period from similar conditions and keep the optimal substructure of the problem. The constraints are presented in Eqs. (12) and (13). Nonetheless, the second constraint should be modified when using rolling horizons or discounted functions with infinite planning periods for other kinds of markets.

$$P_{cl,max} \ge P_{cl,t} \quad \forall t \tag{12}$$

$$\theta_0 = \theta_T \tag{13}$$

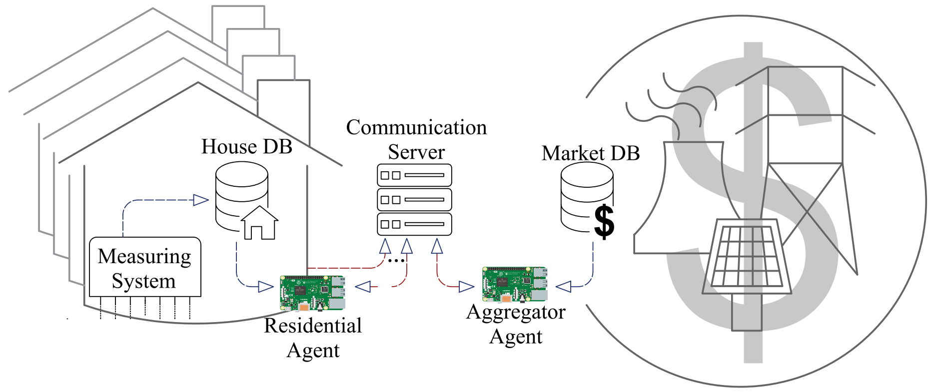


Fig. 6. Data network in a distribution circuit.

4.1. Five residential agents

The first case study contains five houses with the following devices:

H1. Controllable heating system, uncontrollable electrical loads, and solar PV array

H2. Controllable heating system, uncontrollable electrical loads, and solar PV array

H3. Uncontrollable electrical loads and solar PV array

H4. Controllable heating system and uncontrollable electrical loads

H5. Uncontrollable electrical loads

The proposed residential agent architecture with the mentioned load models is enough to overcome residential customers' heterogeneity because the models are trained to produce zero output when there is no data. The consumption data of uncontrollable electrical appliances corresponds to real measures, collected from houses in Trois-Rivières, QC, during the same period as weather data. The solar PV arrays and the heating systems have capacities of 10 kWp and 15 kW, respectively.

In order to apply a sensibility analysis to the parameter δ, all the agents are configured with the same constant value in this TE framework. This parameter only affects the houses with controllable loads and thus, H3 and H5 can be considered inflexible demand. On the other hand, given the convexity of the utility function for heating systems, there is a limited range where changing δ affects the cost of H1, H2, and H4. This range that depends on the parameters of the model (Eq. (10)) is subject to gradual changes from one market period to another because of the adaptive training.

Fig. 7 presents the results of internal temperature for one house with different values of δ where $\theta_{ref} = 21°C$. A customer with high price-elasticity is represented by a low value of δ, which leads to higher deviations from the reference temperature. Such customer undergoes more temperature fluctuations to leverage low price periods by preheating.

The final agreed power demand for $\delta = 0.1$ is presented in Fig. 8. On the last day, the consumption increases due to low external temperature. According to the corresponding planning procedure, the total aggregated demand for the five days should be 2965.77 kW h and the PV surplus 15.38 kW h. Since the planning procedure results in a forward contract instead of a future one, the penalties for deviations should not be harsh for residential customers.

Fig. 9 presents the results related to the price signal based on $\delta = 0.1$. The unitary cost, *UC*, is \$0.04 and the initial cost is \$0.06. It can be understood that when the solar PV arrays are producing energy, the prices reduce in order to incentivize consumption. The iterations stop when the estimated PAR converges with a relative difference between consecutive iterations lower than 10^{-4}.

Table 2 summarizes the final peak-to-average ratios for different price-elasticities within five days. The gap between the actual value and the estimated PAR demonstrates the aggregator's need to improve its model of the residential agents' response. It should be noticed that a lower value of δ increases the peaks not only in the temperature but also in the consumption. However, customers with higher price-elasticities pay a lower final cost and have a bigger margin to adjust the load drivers in the real operation.

4.2. Seven residential agents

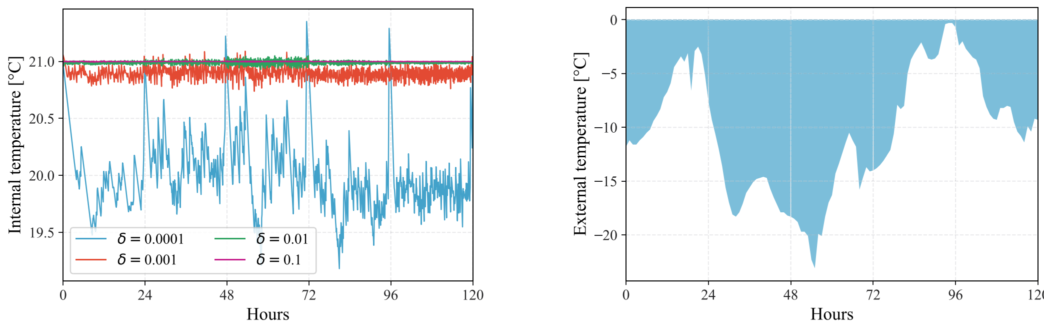
In the next step, two other houses are added to the initial case. These homes consist of uncontrollable appliances and controllable heating systems with the same capacity to examine their contributions to the system flexibility. The other conditions remain equal for the new arrangement. The aggregated energy use increases, but the demand profile has lower PAR. This is due to the new controllable loads contribution to flattening the profile. However, an individual price signal for each customer can be a better approach to shift the consumption when there are different kinds of controllable loads. The demand profile for $\delta = 0.1$ is presented in Fig. 10.

Similarly, the price signal has low values during solar PV production hours. The final cost increases for this case due to the new houses energy consumption. The revenue from the aggregation rate is the same in all cases. The price results for $\delta = 0.1$ are presented in Fig. 11. Furthermore, the entire results for cost and PAR are presented in Table 3.

4.3. Results analysis

The results, presented in Tables 2 and 3, show that elastic users managing controllable loads can reduce the operation cost of an energy system. In this case, users' elasticity is represented by the scaling parameter, δ, of the utility function. This representation is useful to formulate an optimization problem for balancing utility and energy cost in order to find a consumption strategy. The optimization is carried out by an automated agent that gets a forward contract. This, in turn, can simplify the participation of residential customers in energy markets and grant the rationality in the decision process to develop market-clearing mechanisms.

It is relevant to consider that users' elasticity can vary in time.



(a) Estimated internal temperature $\hat{\theta}_{int}$

(b) External temperature

Fig. 7. Temperature conditions of the houses.

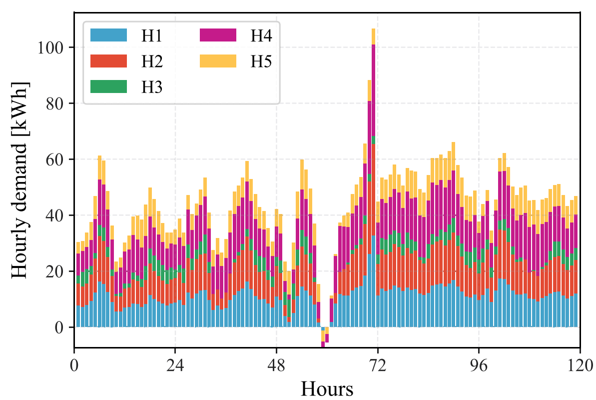


Fig. 8. Aggregated energy demand with five residential agents for.$\delta = 0.1$

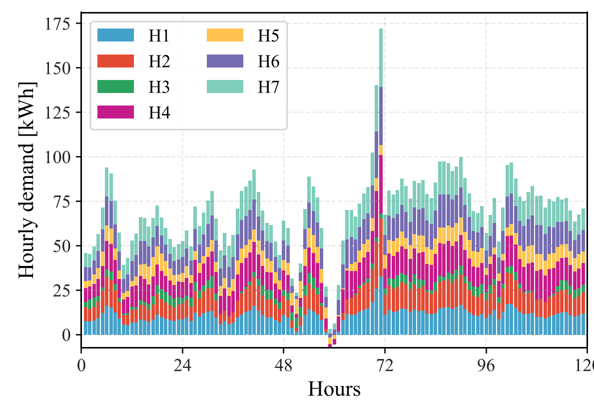
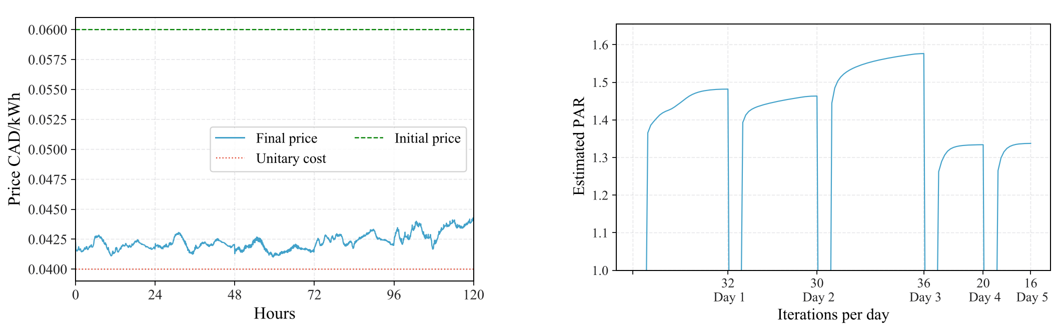


Fig. 10. Aggregated energy demand with seven residential agents for.$\delta = 0.1$



(a) Final prices

(b) Estimation of PAR

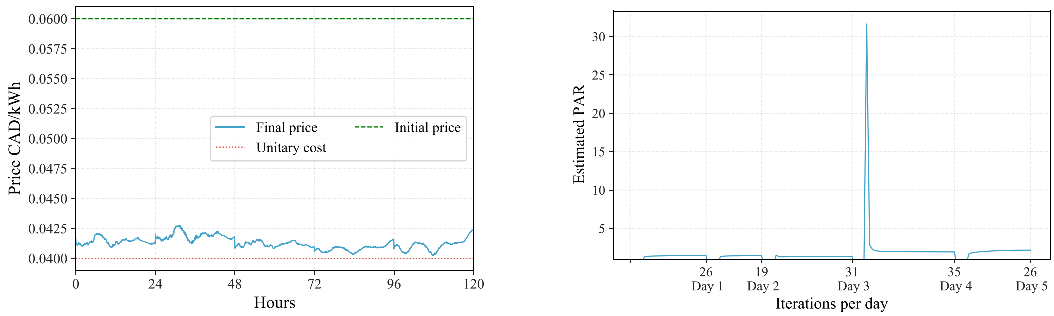
Fig. 9. Negotiations results with five residential agents for.$\delta = 0.1$

Table 2
Final Peak-to-Average ratio at different elasticities with five residential agents.

δ	Day 1	Day 2	Day 3	Day 4	Day 5	Cost [CAD]
0.0001	3.0953	3.7448	4.2460	2.3986	2.7348	119.0689
0.001	2.4247	1.9857	2.9140	1.5243	1.5081	120.6070
0.01	1.8471	1.5520	2.8390	1.2855	1.3470	120.8605
0.1	1.5828	1.3935	2.5551	1.2242	1.3407	125.1178

However, selecting an accurate value of elasticity to perform transactions is not a trivial task for automated agents. A possible solution is to allow users to express their preferences on comfort and cost continuously in order to adapt the problem formulation. Besides, the results of controlling electric heating systems show that a more elastic users bear bigger fluctuations in temperature. Thus, it could be reasonable to add ramp restrictions into the optimization problem because these variations can reduce the lifespan of some heating systems [72].

Another problem existing in the literature, mentioned in Table 1, is the direct interaction between residential users and wholesale energy markets that causes difficulty in coordinating large energy systems. In the simulated transactions, it has been evidenced that residential agents can get contracts by interacting only with demand aggregators since they know the unitary cost of energy and their revenue cap. The advantage of forward contracts is the possibility of having demand estimates, in advance, to plan the system



(a) Final prices

(b) Estimation of PAR

Fig. 11. Negotiation results with seven residential agents for.$\delta = 0.1$

Table 3
Final Peak-to-Average ratio at different elasticities with seven residential agents.

δ	Day 1	Day 2	Day 3	Day 4	Day 5	Cost [CAD]
0.0001	3.0544	3.2389	4.1896	2.3787	2.6406	186.0821
0.001	2.3888	1.9023	2.8923	1.3180	1.4777	187.6408
0.01	1.7408	1.4152	2.6069	1.2800	1.3426	190.3280
0.1	1.5358	1.3744	2.4661	1.2093	1.3400	191.2978

operation towards coordinating several energy markets. Moreover, the historical information about these contracts can be useful to do long-term planning and ensure the adequacy of the resources.

In the aggregator side, there is an estimation error that results in a miscalculation of the PAR as it can be seen in the part b of Figs. 9 and 11. A part of this problem relates to the assumption that P_t is a function of only the instant price π_t. Such situation can be solved by using reinforcement learning techniques that parametrize the residential agents' responses better. One interesting result, useful to improve the aggregator agent's models, is that the convergence rate does not rely on the number of flexible resources. The fact that the price signal is unique for all residential customers can lead to a Prisoner's Dilemma (PD) because it shifts all the flexible resources to consume on the same low price periods.

4.4. Limitations and application opportunities

The proposed agent architecture can be expanded to transact commodities other than active energy. The residential agent needs more models of devices in its local environment to forecast their consumption and know their controllable potentials. However, the general formulation of the optimization problem remains the same (balancing users' utility and energy cost). For the aggregator agent, it is necessary to include other optimization blocks because flattening the demand profile is not of interest to all energy markets. In such a case, it is advantageous to use asynchronous behavior to support multi-objective optimization. This results in agent architectures that contribute to the development of smart energy systems and allow for the integrated operation of all energy grids, involved in the residential sector.

The interaction protocol, presented in this paper, is sequential to ensure the participation of all residential agents. This configuration is suitable for forward-markets but limits the application to other markets such as spot markets where clearing time is crucial. Additionally, the proposed protocol is not intended to permit the communication between the residential agents because it is expected that the aggregator makes the coordination. In future work, it is interesting to analyze the potentials of this interaction protocol to use individualized price signals and avoid PD.

In the above cases, it has been assumed that the system is able to absorb all imbalances because the adequacy of energy resources is out of the scope of this paper. In fact, for addressing this matter, the aggregator agent needs to communicate with higher-level agents in the wholesale market to get an estimate of the unitary cost of energy beforehand. However, the operation of a large energy system ultimately depends on the ensemble of small coordinated systems.

Finally, it is important to mention that the COVID-19 pandemic hastens application opportunities for technologies that engage the residential sector in TE systems. In fact, lockdown measures have increased the energy demand of houses [73]. Even after economic recovery, the residential sector electricity demand is expected to remain higher than before the pandemic [74].

5. Conclusions

In recent years, transactive energy systems have been developed to allow different kinds of grid agents to trade active energy among other services. These systems help retailers and utility companies refine and automate their information process and decision algorithms. Nevertheless, demand-side agents requirements, especially in the residential sector, have not been properly contemplated and their decision-making process has been overlooked. Therefore, it is important to develop automated systems that make decisions and participate in transactive mechanisms on behalf of residential customers. Particularly, the anticipation tasks of prevision and planning must be automated to engage customers into forward-markets.

In this paper, the proposed planning algorithm for residential agents has been implemented through an agent architecture with six behavior. This architecture can be conveniently integrated into a multi-agent system to leverage transactive energy mechanisms and advance towards fully decentralized smart energy systems. Besides, the adaptability character of the proposed architecture allows for overcoming the heterogeneity of residential customers. The developed planning algorithm can be used with different models of controllable and uncontrollable appliances and expanded to participate in other energy markets.

To integrate the residential agent architecture into a transactive energy system, we have presented an interaction protocol to reach equilibrium in a Stackelberg game with a demand aggregator as the leader. This protocol is sequential to ensure all agents participate in the transactions and contract energy for the market period. The suggested strategy for managing the energy system can contribute to scaling market solutions and help analyze complex systems as an ensemble of small coordinated systems. The proposal has been tested by using simulated transactions and actual data of household appliances and electric heating systems, as controllable loads, during winter period. The results have demonstrated that the flexibility of residential resources strongly depends on users' valuations of comfort.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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