Driving Innovation: Prosumer Incentives in Peer-to-Peer Energy Trading

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ABSTRACT

Peer-to-peer energy trading is an innovative idea that overcomes several technological and industrial hurdles. It allows industries and consumers, including knowledgeable prosumers, to trade excess energy with distributed generation sources, such as solar, wind, and electric vehicles, thus promoting a significant reduction in overall energy consumption. Real-Time Pricing (RTP) is increasingly essential in integrating smart home device Demand Response (DR) strategies. RTP improves energy management and enables customers to respond intelligently to price fluctuations. In this vein, this paper proves how DR and peer-to-peer (P2P) energy trading could affect energy prices by allowing producers (consumers) and smart home users to interact directly rather than through the traditional grid. The two-pronged planning approach substantially contributes to the reduction of electricity costs. DR enables P2P energy trading, while deep learning algorithms adapt smart home devices to RTP dynamics. Simulation results show that using P2P energy trading and DR in smart homes can significantly eliminate costs. This hybrid approach increases the energy efficiency of Smart Grid (SG) 2.0 technology and makes it more adaptable and cost-effective.

Keywords-smart grid; advanced reinforcement learning; solar panel array; decentralized energy exchange; energy market

I. INTRODUCTION

The Smart Grid (SG) 2.0 represents a significant energy management advancement. It deploys state-of-the-art artificial intelligence to improve the energy use by integrating distributed energy resources and local networks. This unique framework acts as a self-correcting mechanism, facilitating the efficient transmission of energy. It also offers new solutions with great potential for the energy industry. The energy sector has undergone significant changes due to the rapid industrial growth. These changes include demand patterns, resource use, management approaches, distribution methods and commercial strategies. The rise of prosumers - individuals who are active in both production and consumption of energy - has stimulated the implementation of new energy consumption models [1]. In addition, the large-scale deployment of Renewable Energy Sources (RES), the improvements in operational efficiency and infrastructure, and the widespread availability of innovative services contribute to the energy industry's continued evolution. Many actors, especially energy companies, are adopting new marketing methods and regulatory frameworks to ameliorate operational efficiency. Studies highlight the advanced features of SG 2.0, demonstrating its potential to easily integrate distributed energy resources, artificial intelligence, and grid technologies in response to changes in the energy demand [2]. The advanced technologies in SG 2.0 along with the changing energy consumption patterns and a greater focus placed on RES have improved the operational efficiency and intelligent infrastructure and can completely transform energy systems [3]. Peer-to-peer (P2P) energy trading allows end-users to participate in direct electricity transactions, bypassing traditional utilities and promoting direct communication between customers and suppliers. However, barriers, such as grid constraints and privacy concerns, make the creation of a robust communication network that enables P2P trading within the distribution system imperative [4]. Several experimental startups and research projects are underway to address the issues associated with P2P energy trading.

Photovoltaic (PV) Energy Resources (PERs) enable overgeneration, increasing the energy output even in places where local power generation is limited. PVs are becoming a reliable RES in areas with an energy surplus. Distributed PV systems are gaining popularity in residential areas due to their low cost, high capacity, ease of installation, and low maintenance requirements. Communities that can directly share and consume solar energy can increase the use of PV electricity by encouraging local energy sharing. P2P energy trading in solar PV and positive energy zones is beneficial [5]. Along with outlining the potential benefits, authors in [5] note that

P2P trading within distribution networks raises integration issues. The paper also discusses several global pilot programs and research projects to reduce these difficulties, providing insightful information about further attempts to develop this novel energy idea. The EU Commission's renewable energy budget includes energy communities, which facilitate energy trading across the continent. P2P trading, where customers form energy communities, benefits energy companies. Members of these communities can triple their profits by selling their excess energy [6]. Advanced energy trading models require network infrastructure to facilitate P2P and distributed energy transactions. Adopting legislation that promotes solar energy use and reduces incentives requires careful planning and modeling of P2P business models. Future energy trading should consider these fundamental strategies: limiting third-party responsibility and ownership and defending community and consumer rights [7-8].

In [9], the authors stated that compliance with the new regulations, which focus on promoting the use of solar energy and reducing the reliance on subsidies, is paramount. When evaluating current and future energy trading models, it is essential to carefully analyze potential ownership structures for PV systems. The authors highlight the EU's inclusion of energy communities in the renewable energy budget and the implementation of P2P trading as a novel method for the energy industry. In [10], the authors mentioned that the main concerns are the modification of the grid infrastructure, the improvement of P2P PV business models, and the evaluation of PV system ownership models, all of which depend on solar legislation. In [11], the authors present a business model focused on solar PV technology and highlight the importance of P2P energy trading, community-owned PV systems, and intelligent Demand Side Management (DSM) at home to reduce energy costs. In [12], the authors noted that energy-sharing communities employ community-owned PV systems to promote economically sustainable PV installations as a strategic business strategy. In the early stages of SG research, focus was given on implementing DSM solutions to reduce the energy costs in smart homes. In their study, the authors suggest that DSM does this by shifting loads to periods of reduced tariffs. In [13], the authors noted that the solar PV sector encompasses various economic models, including configuration assessments, the rise of community-owned PV systems, and the beneficial effects of DSM on improving the energy efficiency in smart homes. The authors studied how Software-Defined Radio (SDR) works, how energy storage systems affect consumer trading, and how DSM and P2P trading are linked. Authors in [14] presented comparable customer cost calculations following the SDR methodology. Authors in [15] examined the impact of energy storage systems on consumer-to-consumer trade by comparing the total amount of energy stored with the total amount of energy transferred by all users. Furthermore, in [16], the authors investigated the integration of DSM with P2P trading. In [17], the authors presented a P2P network solution that minimizes energy costs using microgrids, enhancing the value of the locally Distributed Energy Resources (DERs). In [18], the authors examined some aspects of energy and trading systems. In [19], the authors proposed a P2P network approach to reduce energy costs in microgrids and increase the importance of DERs. In [21], the authors examined different strategies for organizing the distribution of grid power and highlighted the usefulness of game theory as a mathematical tool for studying market interactions between customers. In [20], the authors analyzed different approaches in network power control. In [22, 25], the authors considered the contractual difficulties, including those related to maintaining a reliable energy supply. In [23], the authors investigated a multi-agent strategy for managing grid power, integrating the game theory to analyze customer and market relationships. In [24], the authors reviewed contractual arrangements and support techniques to improve energy security and minimize financial losses. In [26], the authors proposed a Demand Response (DR) method using incentives, like time-of-use pricing, real-time pricing, and scheduling of high-use equipment. They also developed a P2P simulation model for different scenarios, such as varying battery power rates and the use of RES.

Compared to the previous works, this work manifests the significant cost reductions achieved through P2P trading and DR methods. By actively empowering consumers to participate in energy markets and optimize their consumption habits, a significant decrease in electricity costs is observed. In addition, incorporating Deep Learning (DL) algorithms improves the flexibility of smart home devices, further increasing energy efficiency. Through qualitative analysis, this study explores the broader implications of its findings for developing innovative grid technology and the transition to sustainable energy systems. The main contributions of the current paper are:

- The creation and planning of smart homes that provide customers with various unique technologies, such as appliances, distributed generators, and electric vehicles.
- The design of two classifications of smart home appliances:
  - Those that regulate temperature.
  - Those that manipulate electricity.
- A Real-Time Pricing (RTP) system is integrated using a DL algorithm to schedule tasks for smart home devices. The impact on user comfort should also be considered. The scheduling algorithm was designed to maintain balance in meeting user requirements. The obtained results prove that the product's active users and non-users do not experience any significant effect on their comfort.

Embracing DR is emphasized in this paper. DR aimed to enable P2P power trading between energy producers or suppliers (masters) and energy users in smart homes (consumers/prosumers). Implementing P2P power trading through DR can result in cost savings for electricity expenses, which benefits suppliers and consumers. The study proposes a solution to the constraints of smart homes by combining P2P energy trading with hardware scheduling. Maximizing energy utilization and cutting costs are critical factors in implementing advanced technologies such as DL and DR for scheduling.

II. METHODOLOGY

A. Distributed Power Sharing Concept

Decentralized power-sharing involves the exchange of electrical power between multiple network nodes. This is common in SGs, microgrids, and small energy communities that distribute and transmit energy. The key components of distributed power sharing include generating electricity from local sources, like solar panels and wind turbines, and allowing network members to trade energy P2P [27]. This feature enables users to sell energy directly, making local power usage more efficient. Distributed power-sharing systems can utilize batteries to store the excess energy and release it when needed, improving load balance and resilience. Smart homes with energy storage, smart meters, and automation are necessary to achieve this goal [28]. These homes can optimize energy usage and participate in energy transfers [29, 30]. Optimization algorithms aid in the efficient energy distribution, minimizing losses, and adapting to energy demand and supply changes. Distributed power-sharing promotes collaboration within communities, encouraging energy independence and sustainability. Tariffs, incentives, and pricing mechanisms encourage individuals to exchange the excess energy or adjust usage during peak hours. Decentralized power-sharing reduces the single points of failure, increasing resilience and reliability. It usually involves utilization of RES, decreasing carbon footprints, and promoting sustainability. It supports robust, sustainable, and efficient energy systems by involving communities in electricity generation, distribution, and consumption through technology and communication [31].

B. P2P Power Sharing

Let us assume an Energy Pool Unit (EPU), Smart Homes (SHA), and Traditional Homes (THA) that share energy in a residential area (see Figure 1), forming a community that can participate in energy-sharing. SHAs have battery (BT) energy storage, which allows them to sell excess energy to the EPU and buy energy at market prices in real-time. The energy backup unit is used to manage the excess and deficit power. During shortages, the EPU sells electricity to the non-market homes at lower prices than those of the retail market. In traditional solar-powered homes, extra energy can be sold to the energy collector for more than the feed-in tariff. Pooled, decentralized agents negotiate purchases and sales. The grid sets selling prices if the residents consume more energy than the P2P market produces (Energy Transactions).

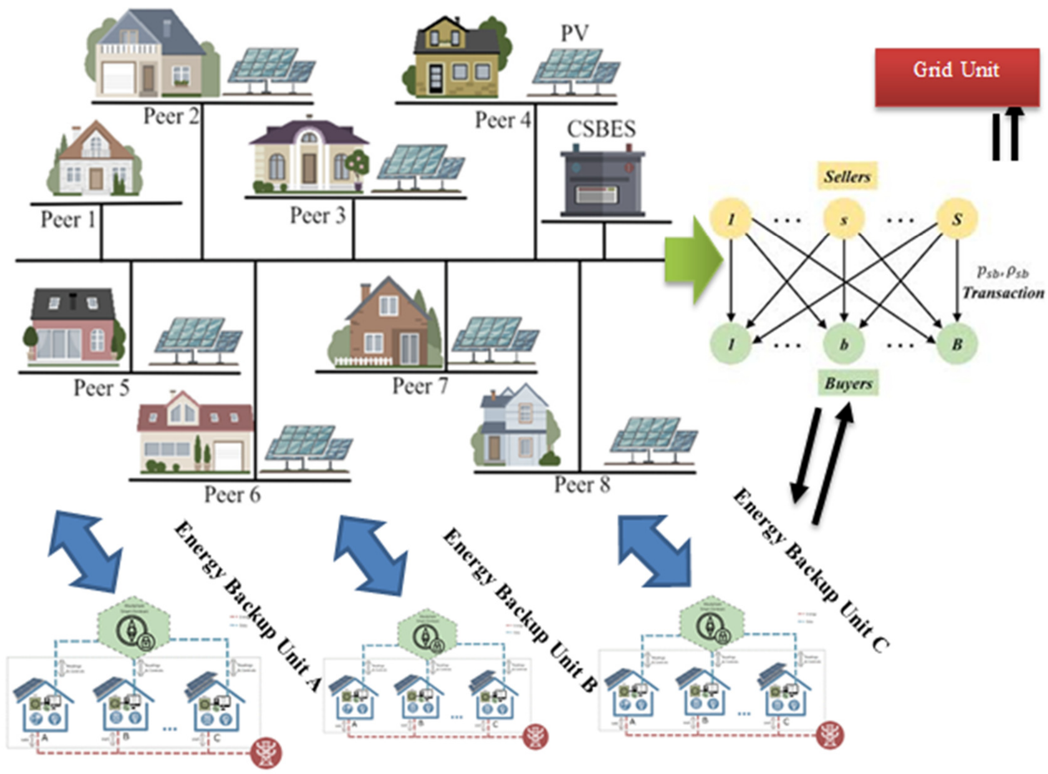

Fig. 1. P2P energy system design.

C. The Energy Pool Unit

This section explains how retail electricity prices in a neighborhood and energy consumption are estimated. The EPU purchases electricity from consumers, Distributed Generators (DGs), and RES. The purchased electricity is then sold on the retail market at a lower price, known as the real-time price. The complex receives power from SHAs and surplus power from DGs. The surplus energy-to-demand ratio determines the power pool's price. Equation (1) predicts the neighborhood's retail price of electricity and power by considering power generation, surplus, demand, and pricing. The equation shows the relationship between variables and can be applied to other settings [32]:

$$\begin{cases} G(t,b(t)) = m(t) + n(t,b(t)) \\ n(t,b(t)) = \alpha(t).(p(t))^2 + \beta(t).b(t) \\ b(t) = \frac{h_m(t)+K_{pv}(t)+g_m(t)}{g_n(t)} \\ n(b(t)) + \varepsilon \prec m(t) \end{cases} \quad (1)$$

where $G(t,b(t))$ indicates the estimated retail market price of electricity and energy consumption, $m(t)$ represents a component of the estimation, $n(t,b(t))$ is another component of the estimation, determined by the couple $(\alpha(t),\beta(t))$, whereas t, $b(t)$ represents a calculation parameter. The condition $n(b(t)) + \varepsilon \prec m(t)$ ntroduces a comparison related to surplus and demand.

D. Single Home Sharing Energy

1) Rooftop Photovoltaic Energy Supply

Rooftop PV energy production uses PV modules to generate electricity. An MPPT (Maximum Power Point Tracking) controller and a DC/DC converter are essential components to achieve this. The production of rooftop PV energy is modeled and controlled by integrating current-generating characteristics. Equation (2) illustrates the rooftop PV energy production process [33]:

$$\begin{cases} (PV - ROOFTOP): I_{Rooftop} = \\ \quad I_{ph} - I_s e^{\left(\frac{N_S.V_{PV}+N_P.I_{PV}.R_s}{V_T}\right)} \\ \quad - \frac{N_S.V_{PV}+N_P.I_{PV}.R_s}{R_{sh}} \\ P^{Roof}(\forall t) = P^{Roof}(s,t) * D(s,t) \end{cases} \quad (2)$$

where $I_{Rooftop}$ stands for the generated current, I_{ph} represents the photocurrent, $I_s e^{(\frac{N_S.V_{PV}+N_P.I_{PV}.R_s}{V_T})}$ represents the factors affecting the current, P^{Roof} represents the power generation, and $D(s, t)$ is a control function.

2) Appliance of Operation Constraints

The term "home restrictions" refers to rules regarding the employment of electric household appliances. These rules are communicated through two binary variables: "1" indicates that the device is currently being used, while "0" indicates that it is not. Each device's usage duration is determined within a specific time frame (see (3)):

$$\begin{cases} D(i,t) = T_{status}(t)(T_{start} / T_{end}) \\ \xrightarrow{1} \text{If } t \ \geq \ \left(T^{start} \text{ and } t \ \leq \ T^{end}\right) \\ D(i,t) = 0 \\ \xrightarrow{2} \text{If } t \ \leq \ \left(T^{start} \text{ and } t \ \geq \ T^{end}\right) \end{cases} \quad (3)$$

The binary variable $D(i,t)$ indicates the current state of the i-th electrical device at a given moment t. Device functioning is indicated by $D(i,t) = 1$ and device inactivity by $D(i,t) = 0$. Each device's operating duration is established within a defined time frame. To optimize energy usage, it is recommended to schedule temperature-dependent loads, such as air conditioners and electric water heaters, with thermostat controls, as outlined in (4):

$$\begin{aligned} & T^{a}_{\text{Ther}}(\text{t}+1) = \alpha\left(T(\text{t}) - T_a\right) \\ & +T_a - (\eta * m(1-\chi)) \end{aligned} \quad (4)$$

where T^{a}_{ther} represents the thermostat-controlled appliances temperature, T_a denotes the initial temperature, $m(1\text{-}\chi)$ represents the thermostat conditioners, and η is a thermostat-controlled parameter.

3) Prosumer / Consumer Power Balance

The energy balance constraints of Prosumers 1 and 2 are reflected in the design. Equation (5) is necessary to balance the energy supply and demand in Prosumer 1 and Prosumer 2. The goal is to provide a consistent and stable power supply to meet the hourly load requirements. It is unclear how (5) relates to these constraints. Energy budgeting equations equate energy consumption or generation per period to energy supply or generation. In this system, consumers are more likely to use and produce electricity. Power generation and consumption vary between customers.

$$\begin{aligned} & P^{offer}(\text{t}) * J_1(\text{t}) + \left[\sum_{i=1}^{i=m} P^{\text{Pro}}(\text{i},\text{t}) * C^P(\text{i}) * D(\text{i},\text{t})\right] \\ & = P^{\text{Required}}(\text{t}) \end{aligned} \quad (5)$$

where P^{offer} is the generation of power, P^{Pro} is the energy demand by the prosumer or consumer, and $P^{Required}(t)$ denotes the load energy demand during the period t.

4) Household Load Consumptions

The maximum instantaneous power flow between the home system and the utility grid is limited by (6):

$$\begin{cases} P^{P^{Grid-Home}}(t,s) = b_1 P^{P^{Grid-Home}}{}_{max} \\ P^{Home-Grid}{}_{max}(t,s) = b_2 P^{Home-Grid}{}_{max} \\ P^{Grid-Home}(t,s) \leq b_1 P^{Grid-Home}{}_{max} \\ P^{Home-Grid}(t,s) \leq b_2 P^{Home-Grid}{}_{max} \\ b_1 + b_2 \leq 1 \rightarrow \forall t \end{cases} \quad (6)$$

where $P^{Grid-Home}(t,s) = b_1 P^{P^{Grid-Home}}{}_{max}$ represents the power flowing from the home system to the utility. $P^{Home-Grid}{}_{max}(t,s) = b_2 P^{Home-Grid}{}_{max}$ represents the power flowing from the utility grid to the home system, $P^{Grid-Home}(t,s) \leq b_1 P^{Grid-Home}{}_{max}$ restricts the power flow from the home system to be less than or equal to $b_1 P^{Grid-Home}{}_{max}$, and $P^{Home-Grid}(t,s) \leq b_2 P^{Home-Grid}{}_{max}$ restricts the power flow from the utility grid to be less than or equal to $P^{Home-Grid}{}_{max}$. At time t, if a grid outage occurs and the matrix event takes a value of zero, the binary variables b_1 and b_2 are forced to be zero. $b_1 + b_2 \leq 1$ enforces that b_1 and b_2 (or both) can be non-zero, but their sum cannot exceed 1. During a grid outage, energy cannot flow to or from the utility grid. This constraint is modeled by:

$$\begin{cases} \overline{P^{Grid-HomeH}}_{\max}(t,s) \le O^T(t,s) \rightarrow \forall t \\ \overline{P^{Home-Grid}}_{\max}(t,s) \le O^T(t,s) \rightarrow \forall t \end{cases} \quad (7)$$

where $P^{Grid-Home}(t,s)$ and $P^{Home-Grid}(t,s)$ represent the estimited energy demand and supply, $O^{T}(t,s)$ denotes the occurred outages at time t and scenarios s.

5) Objective Function

The objective function aims to minimize the capital cost equation and lifetime cost of each home. The objective function maximizes production benefits while considering interdependent elements:

$$\min_a G_1 + \sum_i^{i=m}(1+w)^{(1-m)}G_2 + G_3 \quad (8)$$

The objective function seeks profit and production goals. Equation (9.1) provides the capital cost of G_1, which includes the price of the BT and the expansion of the PV system. Equation (9.2) provides the yearly expenses, while (9.3) represents the daily cost:

$$G_1 = \zeta^{BT}.C^{BT}(t) + \zeta^{PV}P^{pv}(s,t) \quad (9.1)$$

$$\begin{aligned} Y_2 &= C^{BT}(t,s)\left(\psi^{BT}\delta^{BT} + z^{BT}\right) \\ &+P^{pv}(t,s)\left(\psi^{pv}\delta^{pv} + z^{pv}\right) \end{aligned} \quad (9.2)$$

$$Y_3 = \sum_{t=1}^{M^f}\psi.\left[\sum_1^T \Delta v\left(\zeta^1(\mathrm{t,s}).P^{GH}(t) - \zeta^2(\mathrm{t,s}).P^{GH}(t)\right)\right] \quad (9.3)$$

6) Energy Balance

Equation (10) is an energy balance equation demonstrating the energy conservation in a system. It displays the power that the system's gas heater produced at a particular time and under specific conditions.

$$\left| \begin{aligned} &P^{Grid-Home}(s,t) + P^{Roof}(s,t) + P_d{}^{BT}(s,t) = \\ &P_r{}^{BT}(s,t) + P^{Home-Grid}(s,t) \\ &\qquad + \textstyle\sum_{\forall k} \underline{\Delta_k}(0,1)P_k{}^{App}(s,t) \end{aligned} \right. \quad (10)$$

where $P^{Grid-Home}(s,t)$ displays the power that the system's gas heater produced at a particular time and under specific conditions, $\sum_{\forall k}\underline{\Delta_k}(0,1)P_k{}^{App}(s,t)$ is 1 when active and 0 otherwise.

III. ENERGY TRADING COMMUNITY ALGORITHM

A. Markov Decision Process

The section discusses the Markov Decision Process (MDP) in the context of energy trading within a community comprising intelligent and traditional users. The main MDP components are:

- States ($S(i)$): The set of states comprises factors, such as State of Charge (SOC), pricing, and community price.
- Actions (a): Each state's set of procedures includes acts about purchasing or selling varying quantities of electricity in the retail market or local power pool.
- Q-Value Records ($Q(s,a)$): Q-values indicate the anticipated total payoff from selecting an in-state s. Learning entails updating these Q-values by calculating a weighted average of past and current data.
- Q-Learning: Q-value learning is a method in which the agent learns to predict the rewards it might expect from specific actions in various situations.
- Optimal Action Selection: The agent can select actions based on the highest Q-value. The optimal active mixture is determined based on the Q-values. Equation (11) aims to determine the current state(s) and strives to offer the optimal combination of actions based on all rules. Equation (11.1) selects the current state(s) to provide the optimal combination of actions for all laws. Considering different regulations and limitations, this equation probably requires optimization to determine the best combination of actions for a specific collection of states. Equation (11.2) establishes a relationship between the output groups ($N(s)$) and the Q-Value. This equation likely links the output groups from the present state to the relevant Q-values, connecting state-action pairs with their rewards.
- Q-learning Trad-Algorithm-1: This algorithm is a Q-learning-based method created for energy trading within a community comprising intelligent and conventional users. The process entails learning and decision-making based on Q-values, which indicate the anticipated benefits for specific actions in different phases. The essential elements of an MDP for energy trading are states, actions, Q-value records, and the learning process. The equations mentioned propose an optimization procedure to determine the optimal combination of actions and a technique to link the output groups to Q-values. The Q-learning Trad-Algorithm-1 is the proposed system for energy trading among diverse intelligent and traditional customers.

$$\begin{aligned} &\overline{Q}(s,a) \leftarrow Q(s,a) + aV(s,a) + \phi \max Q_s(r_i()) \\ &a = \max Q_s\left(r_i() \xrightarrow{step1} (11.1)\right) \\ &Q(s,a) = \frac{Min(N(s)).q(i,a)}{\sum Min(N(s))} \xrightarrow{step2} (11.2) \end{aligned} \quad (11)$$

The optimization process involves applying the Min($N(s)$) operator to $N(s)$ output sets. In addition, it introduces the value of $q(i,a)$, which represents the aggregate rule i for a specific action a. The subsequent phase consists of executing the action sequence and identifying new states by calculating $H(s',a)$ and changes in Q values. $H(s',a)$ is determined by (12) for the specified pair (s',a). To calculate $H(s',a)$, it is essential to determine the maximum function for the new states resulting from the series of applied actions. This estimate is associated with the anticipated total compensation for the pairings.

$$\left| \begin{aligned} &H(s',a) = \frac{Min(N(s')).\max\limits_{action}(q(i,a))}{\sum Min(N(s'))} \xrightarrow{step3} (12.1) \\ &\Delta Q(s',a) = V(s,a,s') + \phi H\left(s',a()(s,a) \xrightarrow{step4} (12.2)\right) \\ &q(i,a) \xleftarrow{step5} q(i,a) + \beta.\Delta Q(i,a) + w(i,a) \xrightarrow{step5} (12.3) \end{aligned} \right. \quad (12)$$

- Variations in Q value: Q values for new states and actions are computed. An agent modifies its evaluations according to the observable results.

The function $H(s',a)$ represents the most outstanding value, indicating the new state's maximum or total benefit when acting a. It is crucial to establish the optimal course of action in this case. The Q value of the new state is represented by $V(s,a,s')$, which anticipates the total advantage of taking an action in the starting state and transitioning to the next state. The parameter ϕ demonstrates the variations in the value of q, where β represents the learning rate, which determines the step size during the learning process when updating the value of Q based on a new input. The distorted truth value is represented as $w(i,a)$, which illustrates the transformation of truth into action for each rule i. This may involve modifying the truth value based on business rules. $H(s',a)$ outlines the components in determining the maximum function $H(s',a)$ and the variations in the value of Q during the learning process. To update the Q values with new information, the learning rate β and the distorted truth value $w(i,a)$ are essential. The effect of ϕ varies based on the extent of the algorithm or system. Regarding the energy market process, retail prices, community trade prices and excess power/demand, it fluctuates every 30 min. The community reward function $R^c(s,a,s')$ is standardized between 0 and 1 and provided by (13).

$$\begin{aligned} R^c(s,a,s') &= |\pm G^t| * \Delta\gamma(s) - \Delta\gamma(s) * \Delta Rp(s) \\ \Delta P^c(s) &= G^e + G^s - G^t \\ \Delta\gamma(s) &= B^m(s) - B^m(s') \\ \Delta Rp(s) &= B^r(s) - B^r(s') \end{aligned} \quad (13)$$

Algorithm 1: Trad-Algorithm-1

Input: Household electricity use, temperature, Electricity prices (RTP, Time-of-Use), Agent identification status, Community-Based System Status (CBSS), solar output
Output: The maximum function (a,b), $H(s',a)$, Q-value function of state-action pairs, Output Groupings $N(s)$, Q-value Logs, and Optimal Action
Steps:
Initialization
Allocating memory of size G with N
Initializing the preprocess function $Q(s)$
Initializing target networks using $Q(s',a)$
Iterative Loop
for (for every iteration within the range of [1, Max+1], do the following procedures for an episode)
Episode Start:
Set the state to 0 s.
Calculate the output groups $N(s)$
Q-Value Update Loop:
For each q-value in the set $N(s)$, follow these steps:
Apply the convolution function to a range of values within a specified interval
$N(s)$ corresponds to $w[i,a]$.
Update the q-value using:
$q(i,a) \rightarrow q(i,a) + \beta \cdot \Delta Q(a) + w[i,a]$
Iterative Loop
For i=1,2,3,…,n−1, follow these steps:
Update V based on the highest values.
Update Q by utilizing a combination of maximum values and other parameters.
Normalize Q and V using weights $w[i,a]$.
Perform a task in smart home settings and monitor the outcome at time t+1.
Compute:
$\Delta Q(s',a) = V(s,a,s') + \phi H(s',a(s,a))$,
Then add $[ai][aj]+\beta \cdot \Delta Q(a)+w(i)$.
Choose a restricted number of K instances for modification.

B. Multi-Agent Reinforcement Q-Learning

The energy sector could benefit from P2P energy trading and DSM improvements. The issue involves a continuous decision-making process where participants, such as prosumers and consumers, decide on energy exchange and load control technology. The energy market is characterized by unpredictability and continual change, which complicates decision-making. P2P energy exchanges and DSM are crucial components of the energy market and are significant in managing intermittent access to public information. Making precise and dependable selections in this situation is challenging due to the constantly evolving energy industry.

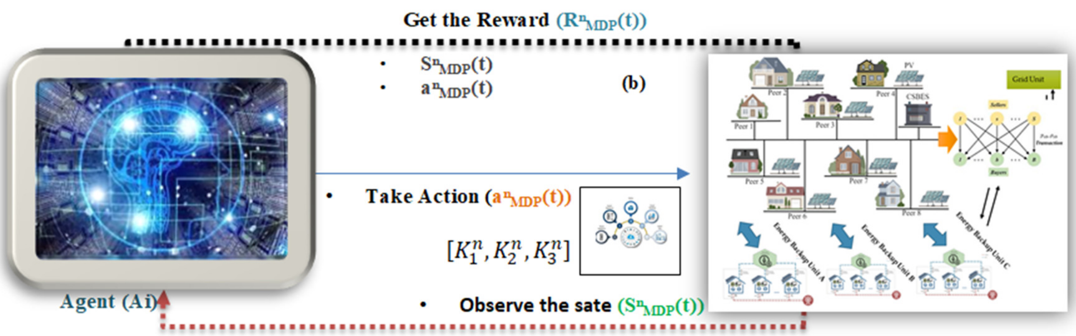

Fig. 2. Agent and environment interactions.

IV. CASE STUDY

This section analyzes a renewable energy project implemented and evaluated in a Saudi Arabian community. The project involved 9 community members, including 4 prosumers, 2 clients, and an existing PV system. The research gathered time series data, technical and financial details of the technologies employed, and assumptions and optimizations inside the intelligent grid. The prosumer's involvement with the renewable energy pool, energy production and consumption, and their view of the system's user-friendliness were considered. The following essential aspects were contemplated:

- The consumer collected data from the two participating customers.
- The influence of RES on energy use and costs.
- The efficiency of the existing PV system, its impact on the overall energy output, efficacy, and any barriers or achievements encountered during testing.
- The time series data should be examined to identify patterns and trends in energy production and usage.
- System's peak hours, fluctuations, and any notable events that may have impacted it.
- The technical specifications of the RES, including the solar setup, storage systems, and any other components integrated into the smart grid.

This section examines the technical characteristics of RES, focusing on solar installations, storage systems, and other components integrated into the smart grid. The financial components of the project, including the original investment, continuous expenses, and any savings or income generated by the renewable energy pool, are also assessed .

A. System Initialization

The experimental participants are single-household models equipped with ESS batteries and PV systems. These models replicate actual domestic energy systems found in the real world. The studies are conducted in a controlled environment using specialized modeling software to assess RES systems. The software accurately simulates the dynamics of energy generation, storage, and consumption.

PV system sequencing: The sequence in which the PV system operates and the daily requirements of the equipment are observed and documented. Data patterns, peaks and trends are analyzed to understand energy generation and consumption patterns. An analysis is conducted to evaluate the cost reduction of storing renewable energy. The study considers three scenarios: minimal (less than 50% reduction), moderate, and substantial (up to 50% reduction). Each scenario shows different levels of increase in storage capacity.

Calculation of total system cost: The total cost of each system, including PV, energy storage, and state-of-the-art grid components, is calculated separately for each situation. The cost-saving effects of renewable energy storage are analyzed, considering peak periods, volatility, and notable events.

Control groups: Each experimental scenario is compared to a baseline scenario without ESS, allowing the additional cost-saving benefits of RES storage to be assessed.

Total system cost calculation: The total system cost calculation illustrates the cost-reducing effect of renewable energy storage on the total system cost. The study identifies cost-effective thresholds and highlights the importance of optimizing storage capacity by considering multiple factors and variables in the cost calculation.

The experimental results demonstrate the effectiveness and superiority of incorporating energy storage technologies into renewable energy installations. The analysis reveals that renewable energy storage reduces overall system costs and increases energy use efficiency. Energy storage systems increase the stability and cost-effectiveness of renewable energy by reducing peaks, volatility, and the impact of significant events. The study also stresses the importance of optimizing storage capacity for the most critical cost reductions. The significance of regulatory or commercial frameworks that promote the sale of energy, thereby strengthening the financial viability of renewable energy investments, should be emphasized.

Figure 3(a) depicts the solar radiation and the temperature of the environment. It examines the selected days for measuring solar radiation (W/m²) and ambient temperature (°C). Figures 3(b) and 3(c) illustrate the energy consumption on cloudy and sunny days. They detail the load consumption patterns. Figure 3(e) portrays the primary grid outages in Saudi Arabia. It showcases the impact of these outages on the RES system. Figure 4(f) presents the Time-of-Use (TOU) and RTP into the simulation and explores how different pricing models affect the decision-making process of the renewable energy system. The simulation period is 2022.

B. Case Study: Grid without Blackouts

The proposed approach focuses on integrating renewable energy technologies, such as solar arrays and energy storage systems.

Figure 4 displays the effectiveness of integrating storage and maintaining power system stability. The proposed approach suggests that a storage system should only be combined if the current electrical system functions correctly. Figures 4(a) and 5(b) disclose the daily operational interpretation, illustrating the sequence of the PV system and total appliances with ESS batteries during a standard day. Figure 4(a) explains how PV and ESS systems meet the home's energy needs at midday. At the same time, the grid can provide additional electricity during peak demand periods (see Figures 4(c) and 4(d)). The relationship between renewable energy storage and cost reduction is demonstrated through multiple scenarios on different scales (small, medium, and large), analyzing the relationship between storage capacity and cost reduction. Using a single-home model to calculate costs shows how it can be deployed to determine the total cost of each system in scenarios where homes do not have shared energy. The elements contributing to these cost estimates are analyzed. The trading algorithm was incorporated to calculate the cost of trading between the homes and the utility.

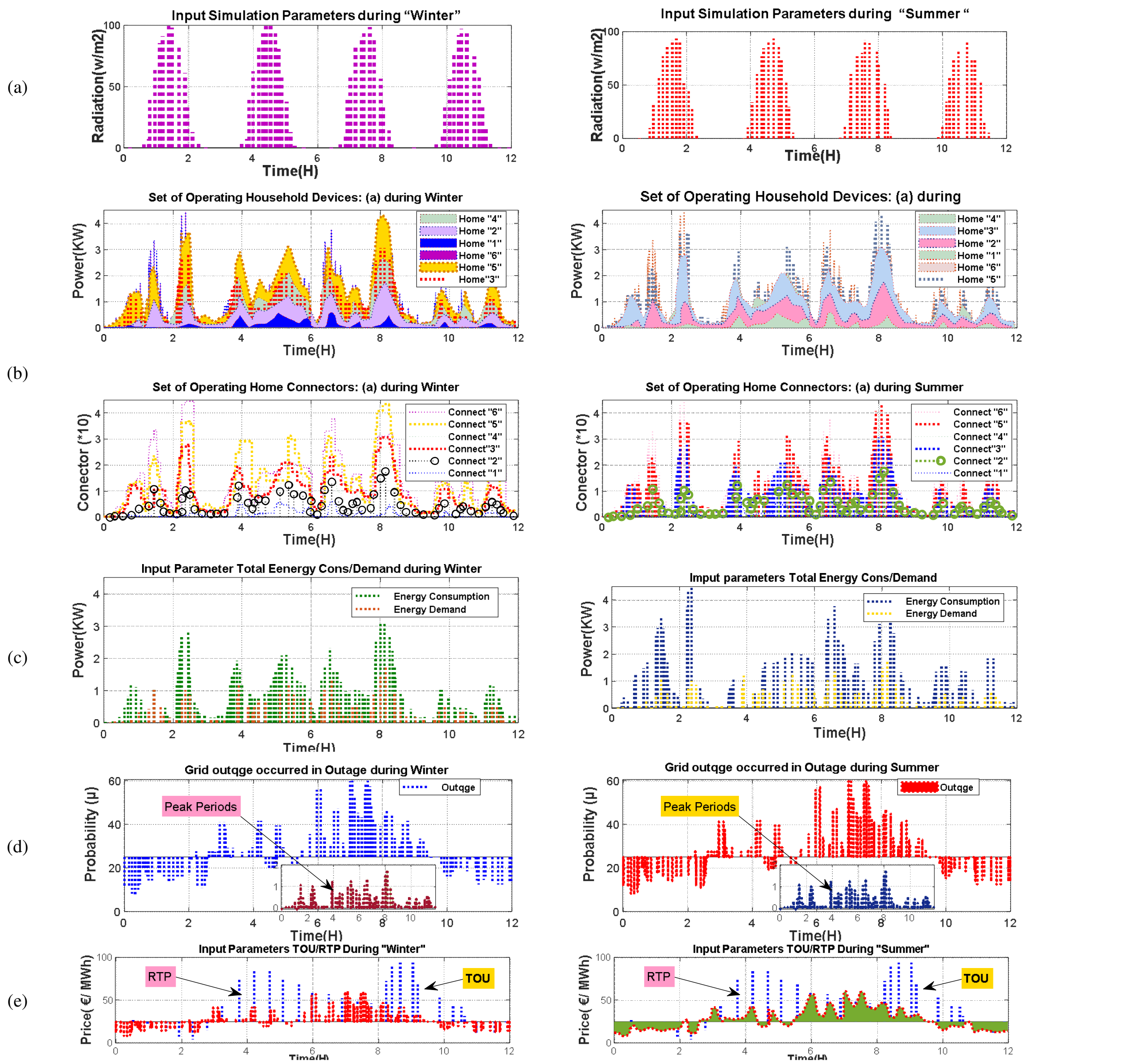

Fig. 3. Representative days taken: (a) Solar radiation (W/m^2) and ambient temperature (^{0}C), (b), (c) Load consumption and total load consumption, (d) The data available for the main Grid breakdowns occurred in KSA, (e) TOU and RTP prices considered in the simulation.

Figure 4(e) depicts the energy savings associated with the grid and energy thresholds. Figure 4(e) displays the energy savings to the grid due to the price difference between the household systems and the utility. It outlines the charging processes, energy prices, and suggested methods for the households to maintain energy levels above the minimum threshold. The trade-offs are analyzed, highlighting how inefficient charging can increase energy costs. High storage penetration rates do not significantly impact savings beyond a certain threshold. Table I discloses the obtained results without blackouts.

C. Case Study: Grid with Blackouts

Figure 4(a) provides the daily operation of a battery-powered PV system with TOU and RTP. The system promotes energy storage to reduce grid dependence. Household demand and solar irradiation describe how the PV system responds to daily changes in solar irradiation. Figure 5(b) demonstrates how the system meets the household demand in sunny conditions and manages energy storage in cloudy or low-irradiation conditions (typical day without blackouts).

TABLE I. OBTAINED RESULTS WITHOUT BLACKOUTS

Cases	Objective Function			PV(kW)		P^{ESS} (kW)
With	TOU	ESS	1931.00	2.899		0.000
PV/ESS	RTP	ESS		3789.00	4.897	0.000
Without	TOU	----		44688.00	---	---
PV/ESS	RTP	----		5976.00	---	---

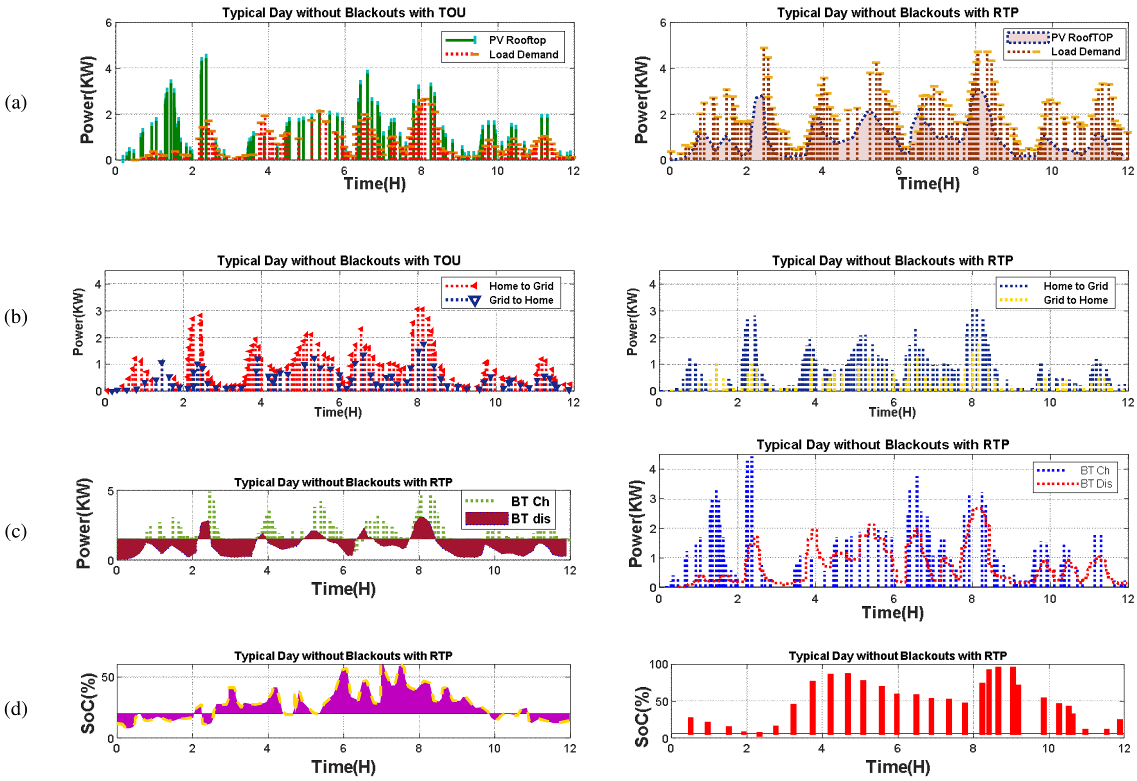

Fig. 4. Typical day without blackouts: (a), (b) Energy demand scheduling result with RTP TOU tariffs, (c) battery charging and discharging, (d) BT SoC with RTP and TOU tariff.

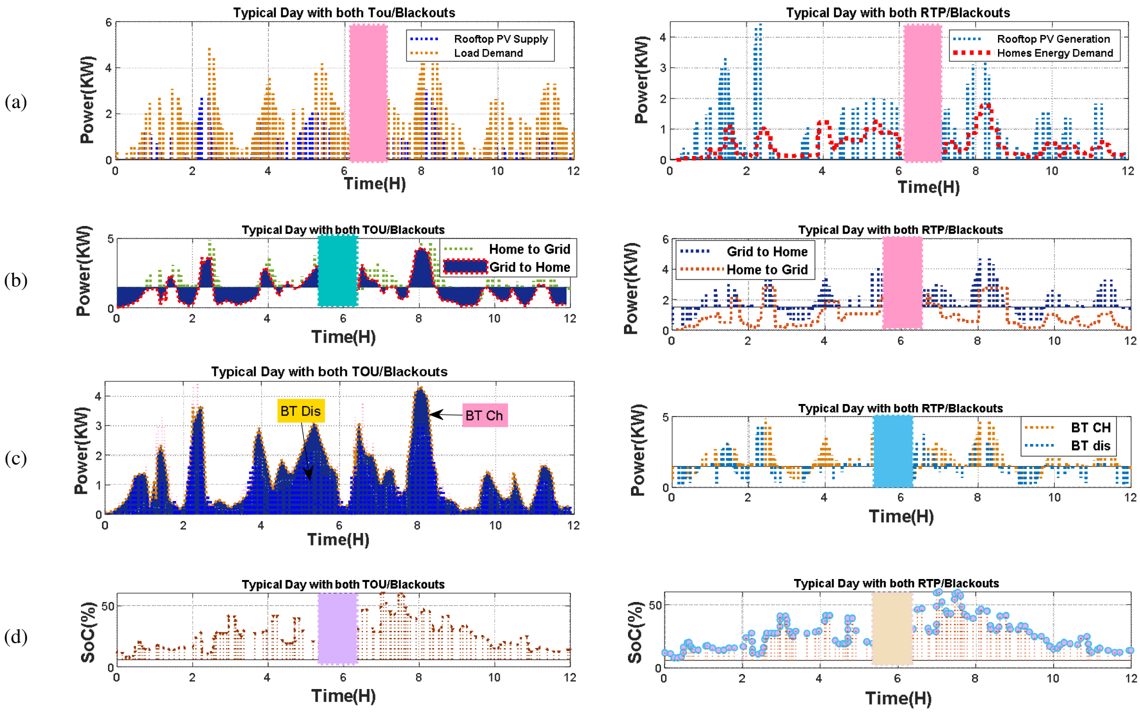

Fig. 5. Typical day with blackouts: (a), (b) Energy demand scheduling result with RTP TOU tariffs, (c) battery charging and discharging, (d) BT SoC with RTP and TOU tariff.

Figure 5(c) exhibits the reduction in grid dependency due to the presence of the battery storage system. It shows the BT charging/discharging cases and proves how the system efficiently uses stored energy to meet household demand during power without outages. It additionally explains how the battery is discharged at expensive times (evenings and nights) to meet household demand when grid electricity costs are high. The system optimizes energy consumption in the afternoon when the energy costs are lower. Figure 5(d) portrays the BT State-of-Charge (SoC%) during the RTP and TOU tariffs.

The comparison with cases without PV and batteries highlights the importance of considering PV and battery results. It examines the performance and benefits of the system, such as resilience to power outages and cost savings through efficient energy use, compared to the scenarios without PV and battery integration. Such a system can benefit residential energy consumers. Table II reveals the obtained results.

TABLE II. OBTAINED RESULTS WITH BLACKOUTS

Cases	Objective Function			PV(kW)	P^{ESS} (kW)
With PV/ESS	TOU	ESS	6235.00	3.256	0.000
	RTP	ESS	3245.00	3.007	0.000
Without PV/ESS	TOU	----	5998.00	---	---
	RTP	----	5987.00	---	---

D. Daily Performance Results

Figure 6 presents how Time-of-Use (TOU) and RTP affect the behavior of each node (λ-Connect) in the proposed technique. Understanding individual energy management during TOU and RTP helps to clarify how each home manages energy consumption. In Figure 6(b), the energy exchange between home and grid during TOU /RTP tariffs is displayed. Households with higher rated capacities exceed the surplus, requiring the PV system to handle the extra load. Effective energy limit management prevents many households from exceeding the limit. In this vein, Figure 6 discusses the benefits of customers and prosumers. TOU/RTP modes focus on node TOU and RTP verification, demonstrating the method's scalability and reliability across different pricing models. Figure 6(c) interprets the total cost during RTP/TOU. The findings reveal that House 1 imports energy free of charge from 6:00 to 11:00 and from 16:00 to 19:00 to reduce supplier dependence. This Figure explains the impact of BT penetration in the total cost during RTP/TOU. House1 has reduced its energy consumption from its supplier during high tariff periods (up to 11.99 p/kWh and 24.99 p/kWh). At 7:30 am, the rated capacity of the dwellings (Lect-Connect3, Lect-Connect4, and Lect-Connect5) exceeds the surplus, forcing the PV array to meet the demand.

E. Annual Performance Results

Table III analyzes how the annual consumption of a house affects the percentage of EMS cost reduction for the entire community. The obtained parameters prove that the EMS nodes consume most of the additional generation internally as the load increases.

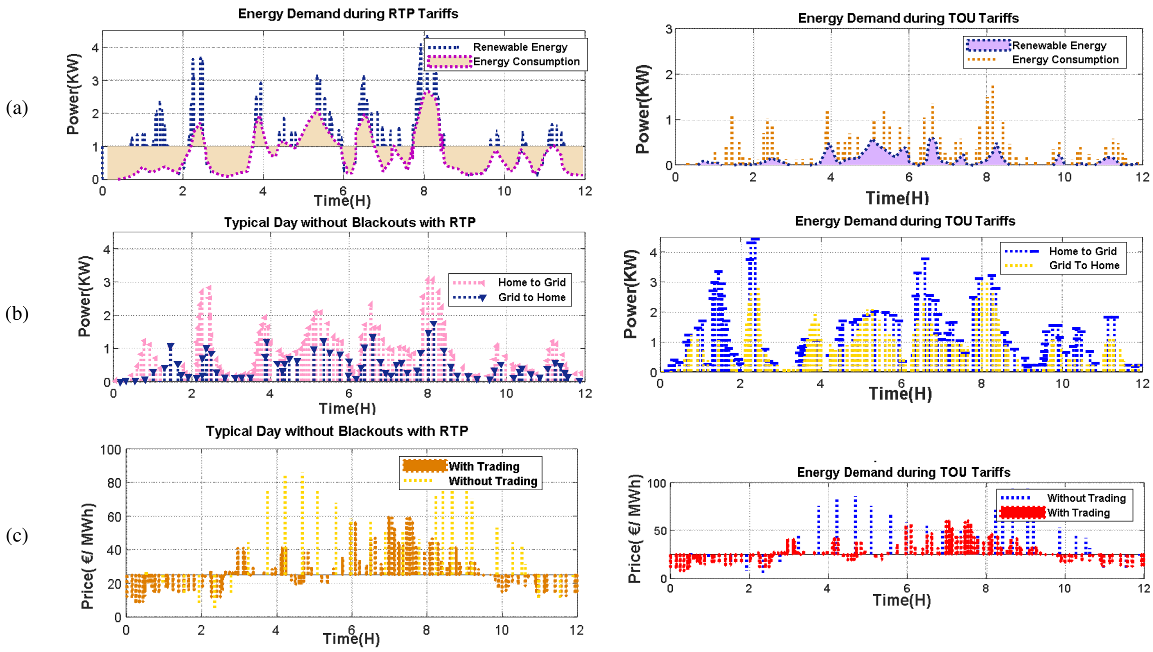

Fig. 6. Typical day with TOU/RTP: (a) Renewable energy / energy demand scheduling result with RTP TOU tariffs, (b) Grid to home/home-to-grid with RTP and TOU tariff, (c) energy trading.

TABLE III. ANNUAL CONSUMPTION DURING RTP AND TOU TARIFFS

Couples	Daily energy cost ($)						Single home operation	P2P operation	Reduction (%)
	Home 1	Home 2	Home 3	Home 4	Home 5	Home 6			
Home 1,2	0.9	1.56	1.500	1.588	1.234	1.220	1.45537	1.52557	8.10002
Home 1,3	1.09	0.89	0.885	0.845	0.666	0.742	1.55557	1.885294	7.4566
Home 1,4	1.089	1.68	0.886	1.786	1.782	1.565	1.2225	1.78002	5.45623
Home 1,4	1.567	0.9	0000	0000	0000	0000	1.0068	1.35689	3.12391
Home 2,5	0.568	1.09	0000	0000	0000	0000	1.00694	1.89713	6.49854
Home 2,6	0.7895	1.089	0000	0000	0000	0000	1.56712	1.00255	5.78242

F. Discussion

An innovative and dynamic community with a shared energy pool is capable of reducing monthly energy costs. The current study proposes a pricing strategy and explores the enhancement of Q-learning in SG 2.0. The proposed methodology seeks to prove effectiveness based on the following points:

- The proposed pricing strategy: The used pricing model reduces monthly energy costs for energy-only users and improves profitability for energy customers. The pricing strategy explores the use of Q-Learning in SG 2.0 for community energy trading. The studied cases describe how home-based renewable energy production is improved for consumers, focusing on efficiency. A community energy aggregator reduces electricity costs and allows knowledgeable customers to benefit from the sale of excess energy.
- Going from prosumer to prosumer: SG 2.0's cutting-edge storage and control capabilities enable customers to become prosumers. Consumers can influence energy costs and increase revenues by engaging in the energy market.
- Q-learning for persistent problems: Q-learning addresses SG 2.0 issues and adapts to energy fluctuations.
- Energy consumption comparison: Analyzing the energy consumption of all consumers can reveal trends. Exploring these areas will provide a comprehensive understanding of the proposed energy management system, its cost-saving impact, and its enhanced effectiveness.
    - Results for scenarios with and without PV and battery technologies are compared.
    - The algorithm's functionality in the presence and absence of RES is proven.

G. Limitations

The developed intelligent energy community relies heavily on smart homes and expects efficient adoption of renewable energy technologies. Although smart homes have the potential to facilitate energy sharing and optimization, their practicality and scalability may be hampered by variables, such as high upfront costs, technological barriers, and the rate of consumer adoption. In addition, the effectiveness of pricing strategies may be influenced by regional regulations and market conditions, which may create barriers to widespread implementation.

V. CONCLUSION AND FUTURE WORK

This paper suggests creating a smart energy community for sharing energy within a neighborhood. The novel energy community structure includes a local energy aggregator, smart households, and non-smart consumers, emphasizing neighborhood energy sharing. The proposed design showcases the advantages of renewable energy by selling the surplus energy, emphasizing its contribution to sustainability and energy production. The study shows how pricing strategy affects community energy transactions in Time-of-Use (TOU) and Real-Time Pricing (RTP) situations, including energy demand and surplus generation.

Future work should explore the potential for intelligent energy communities to be scaled up and adapted to different neighborhoods and regions. The feasibility of the proposed energy-sharing model in different socio-economic contexts and regulatory frameworks, which will provide insights into potential barriers to implementation, could be assessed. In addition, the incorporation of cutting-edge technologies, such as blockchain and IoT, which can enhance the effectiveness and clarity of energy transactions within the community, could be investigated.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available in [33, 34].

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