Real-Time Energy Management of a Microgrid using MPC-DDQN Controlled V2H and H2V with Renewable Energy Integration

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Abstract

This paper presents the design and implementation of an Intelligent Home Energy Management System (IHEMS) in a smart home. The system is based on an economically decentralized hybrid concept that includes photovoltaic (PV) technology, a proton exchange membrane fuel cell (PEMFC), and a hydrogen refuelling station (HRS), which together serve as components to provide a reliable, secure, and clean power supply for a single, smart home. The proposed design enables power transfer between Vehicle-to-Home (V2H) and Home-to-Vehicle (H2V). This allows electric vehicles (EVs) to function as mobile energy storage at the grid, facilitating a more adaptable and autonomous grid. Indeed, our approach employs Double Deep Networks (DDQN), a particular variant of DQN, for adaptive control and forecasting. A Multi-Agent System (MAS) setup coordinates actions between home appliances, Energy Storage Systems (ESS), electric vehicles (EVs), and hydrogen power devices to ensure effective and cost-saving energy distribution for users of the smart grid. The design validation is carried out through MATLAB/Simulink-based simulation using meteorological data from Tunis. The results prove that the V2H/H2V system, provided with AI-based learning and hydrogen power technology, improves residential energy systems' utilization, reliability, and cost-effectiveness

Keywords:

Intelligent Home Energy Management; Hydrogen-Powered Ener gy Systems; Vehicle-to-Home and Home-to-Vehicle; Double Dee p Q-Learning; Autonomous Hybrid Energy Framework; Multi-Ag ent System Coordination
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1. Introduction

The world faces one of its most significant problems related to the energy crisis. The crisis is due to the growing demand for electricity and the depletion of traditional fossil fuels like coal, natural gas, and oil. These conventional fuel sources are susceptible to depletion and contribute significantly to greenhouse gas emissions, which are detrimental to the environment. Consequently, solar and wind energy has emerged as substantial alternatives to address these challenges. Solar energy has attracted particular interest due to its sustainability, availability, and wide range of applications in industrial and domestic sectors [1]-[2]. Solar systems are inherently intermittent, as their power output cannot be consistently sustained, particularly under low-radiance circumstances at night or during overcast weather. The energy crisis is a significant global issue due to the incessant increase in electricity use and the depletion of conventional fossil resources, such as oil, natural gas, and coal. Fossil fuels are finite, and their extraction contributes to greenhouse gas emissions and environmental degradation. Consequently, leading experts have identified solar and wind energy as vital solutions to these challenges. Solar energy is a category of energy source that has been extensively researched and developed in recent decades due to its sustainability, accessibility, and applicability across various industries and household sectors. Despite their numerous advantages, solar systems are inherently intermittent and unable to provide electricity when irradiance diminishes, particularly during nighttime or overcast conditions [3]. Energy As the world turns to greater use of renewable energy, there needs to be a way to store energy to get it to where it's required reliably. To even out supply and demand, scientists have investigated numerous energy storage methods, including electrolysers, batteries, hydrogen storage tanks and supercapacitors [4]. One such environment-friendly and efficient technology is the DOFC-PEMFC portable hydrogen energy system. Hydrogen is the closest thing we have to an ideal energy storage method when there are low levels of renewable energy and high demand. That's because it has plenty of energy density and storage capacity. Hydrogen is very adaptable. For example, proton exchange membrane fuel cells can be applied to hydrogen refuelling stations, flexible solar panels, etc. This, he points out, is evidence that a house can produce an enormous amount of energy independently [5]- [6].

The problem is that because the sources are inflexible or rigid, standalone installations of these renewable energies can't respond to variations in our energy demand. Vehicle-to-grid technology and hydrogen cars enable attractors to obtain and consume energy simultaneously [7]. These fresh concepts would enable smart houses and electric vehicles to communicate in a steady power current. When the electricity supply is lost, an electric car can continue running by feeding power to a vehicle-to-home (V2H) power system or drawing extra power from the home to use later (home to vehicle, H2V). This is what technology can do for you: make your life simpler, relieve you of the

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responsibility when life is hectic and enable you to use your energy effectively in your household [8].

Moreover, current research indicates that smart home apps facilitate users' production, storage, and consumption of energy. Advanced energy management systems EMS are crucial for integrating smart home components with renewable energy sources, energy storage, electric vehicles, and communication functionalities [9]-[10]. Various regulatory techniques have been proposed, including real-time load scheduling and managing certain appliances. The present configuration of most existing systems lacks the requisite flexibility and speed to respond to unforeseen events in real-time. The notion of unique hydrogen, regarding the energy exchange between electric cars and smart home management systems, has insufficiently tackled the integration of hydrogen with EV-based energy exchange [11]-[12].

This effort seeks to introduce an innovative approach for smart homes to meet their energy needs by using technology to capture energy generated from renewable sources, such as hydrogen, and enabling energy exchange for electric vehicle owners. Our approach is expected to achieve flexible and independent energy management by integrating solar photovoltaics, PEM fuel cells (particularly those with hydrogen refuelling capabilities), and bi-directional V2H/H2V power exchange. The system employs a hybrid DDL algorithm integrating DDQN and a MAS to facilitate the efficient collaboration of all energy components. The main goal is to create household energy systems that are more resilient, adaptive, and economical in reaction to variations in demand and supply. We will accomplish this by thoroughly examining the systems utilising real-world data per the specified assessment methodology.

1.1 Literature review and contributions

In [13], the authors underlined the importance of hydrogen energy systems and Proton Exchange Membrane Fuel Cells (PEMFC) as efficient long-term storage solutions for inte-grating renewable energy. Nevertheless, the primary aim was to employ them in pro-fessional environments rather than homes. This study introduces a Hydrogen Inte-grated Management Approach (HIMA) to tackle this problem. HIMA is advancing the integration of a hydrogen refuelling station and a PEMFC as reliable backup power sources within a singular smart home.

In [14], the authors investigated solar and wind power integration in residential energy systems. The focus was on handling intermittent renewable energy sources and the mismatch between consumption and demand. This study introduces a Hybrid Sys-tems Approach (HSA), which couples solar photovoltaic technology with hydrogen storage. It also provides a proton exchange membrane fuel cell (PEMFC) as a backup to tackle the abovementioned issues. This technique is guaranteed to deliver consistent power output and employs a hybrid operating system developed for smart homes.

In [15], the authors reviewed different battery, ultracapacitor and hydrogen storage tech-nologies. The review found that there is currently inefficient real-time interaction between these systems for real-time energy management. The contribution of the present paper is the Smart Storage Coordination Approach (SSCA), a multi-agent system that addresses this limitation. Each storage unit operates autonomously, yet collectively, they function to regulate energy usage. The sharing and cooperation of storage units are time-sensitive, and synchronisation is required only if they are to be used concurrently.

In [16], the authors presented V2H and H2V technologies as flexible energy exchange mechanisms but did not fully integrate them into hybrid systems. To address this issue, this study introduces the Bidirectional Vehicle Energy Exchange Approach (BVEEA), which enables electric vehicles to act as active storage components within the home en-ergy management system, supporting energy supply during peak demand and energy absorption during surplus.

In [17], the authors introduced MAS architectures as practical tools for managing distrib-uted energy resources. However, their studies did not consider the interaction between hydrogen storage, EV energy exchange and renewable generation in a smart home con-text. This paper proposes the Cooperative Energy Management Approach (CEMA), where MAS actively manages the cooperation between hydrogen systems, EVs, PV generation and home appliances for optimal resource allocation.

In [18], the authors implemented reinforcement learning algorithms to enhance energy planning but encountered delayed convergence and scalability issues in hybrid systems. Based on an experimental database, the Adaptive Scheduling Learning Approach (ASLA) has been created and deployed to boost flexibility and learning speed. It em-ploys advanced Double Deep Q-networks (DDQN) to enhance energy scheduling deci-sions among various power sources and storage systems.

Table 1. Comparison of Related Works and the Proposed IHEMS

Approach	Hydrogen Integration	V2H / H2V Support	MAS Coordination	Learning Method	Real-Time Control
HSA	Yes (Hydrogen + PV)	No	No	None	No
SSCA	Yes (Multiple storage)	No	Yes (Storage agents)	None	Partial
BVEEA	No	Yes (Basic V2H / H2V)	No	Rule-based control	Partial
CEMA	No	No	Yes (Resource	Reinforcement Learning (RL)	Yes

			coordination)		
ASLA	No	No	No	Advanced DDQN	Yes (Limited)
PELA	No	No	No	DDQN (DDL-based)	Yes (Limited)
Proposed IHEMS	Yes (Full Integration : HRS + PEMFC)	Yes (Full V2H / H2V integration)	Yes (MAS-based for all components)	DDQN (Double Deep Learning)	Yes (Fully Real-Time)

In [19], the authors adopted DQL for energy management optimisation; however, they did not apply it to hydrogen-integrated or bidirectional EV systems using actual cases and real databases. This study presents the Predictive Energy Learning Approach (PELA), which utilises Double Deep Learning (DDL) with DDQN for intelligent real-time decision-making throughout the hybrid smart home system's components.

In [20], the authors concluded that no comprehensive solution integrates hydrogen refuelling sta tions, V2H/H2V energy exchange, MAS coordination and AI-based scheduling into a unified energy management framework. This paper addresses this research gap through the Integrated Smart Energy Management Approach (ISEMA), which combines all these technologies into a Real-Time Embedded Smart Energy Management System, providing scalability, adaptability and sustainable operation for the next generation of smart homes. Table 1 compares the proposed IHEMS with existing approaches and shows that only IHEMS fully integrates hydrogen storage, V2H/H2V, MAS coordination, DDQN learning and real-time smart home energy management control.

1.2 Contributions

Our purpose was, in contrast to prior efforts, to develop an Integrated Home Energy Management System (IHEMS) that is currently unavailable, aimed at providing smart homes with clean, reliable, and sustainable energy by integrating a hybrid system utilising photovoltaic (PV), proton exchange membrane fuel cells (PEMFC), and hydrogen refuelling stations (HRS) into a singular system. The V2H and H2V operations as unidirectional CHN can facilitate energy transfer between electric vehicles. Power sources, storage systems, electric cars, and domestic appliances within the MAS framework can operate collaboratively in real time. Double DDQN enhances schedule management, rendering the framework more adaptable and efficient. Actual meteorological data from Tunisia are utilised in MATLAB/Simulink simulations to demonstrate the system's validity. It fully complies with the requirements of intelligent home energy management systems regarding energy efficiency, dependability, and load shedding

1.3 Paper outlines

The paper is organised as follows: Section 1 examines the global energy crisis, the imperative for sustainable energy solutions, and the justification for employing hydrogen, V2H/H2V, and advanced control systems in smart homes. The article provides a comprehensive overview of the latest findings in the field. The study in question significantly contributes to the field, especially in adaptive energy scheduling, hydrogen integration, and real-time coordination. Section 2 outlines the IHEMS by detailing the interaction of photovoltaic (PV) systems, proton exchange membrane PEMFC, HRSs, dual-energy storage systems, and MAS utilised in decentralised control. Section 3 clarifies the intelligent decision-making system that uses a MDP and is augmented with DDQN learning. Our work clarifies the architecture of the neural network, the control method, and the roles of all agents. The essay clarifies the grid configuration, the simulation platform, and the climate data from Tunisia employed to assess the system. Section 4 of this essay delineates the findings that have been reached.

2. Autonomous hybrid system of the smart Home Energy

This study presents an autonomous IHEMS that integrates a photovoltaic system, a proton exchange membrane fuel cell, and a hydrogen refuelling station to provide intelligent home applications with a dependable, stable, and efficient electrical energy source. The system acknowledges that solar electricity is not consistently accessible, especially at night and on overcast days or when sunlight is diminished. It achieves this by integrating renewable power with hydrogen-based energy recovery while controlling flexibility and storage options. In the suggested setup, the photovoltaic system is the primary energy source, consistently operating at its Maximum Power Point (MPP) to maximise energy output. The PEMFC extracts hydrogen from the HRS and may serve as an exceptional peak power producer, assisting when the CHPs surpass demand and fulfilling residential requirements during periods of high demand. This hybrid methodology guarantees continuous power supply and enhances the resilience of the smart home energy system. Energy surplus and deficit mechanisms are examined with dual storage layers: a long-term Energy Storage System (ESS) for prolonged backup during low generation periods and a short-term Ultra-Capacitor Storage System (USS) to rapidly modulate power demands relative to the load. This dual storage solution enhances system responsiveness and offers greater flexibility in operational methods. A MAS-based real-time embedded energy management system governs the control and coordination of these hybrid artefacts [22].

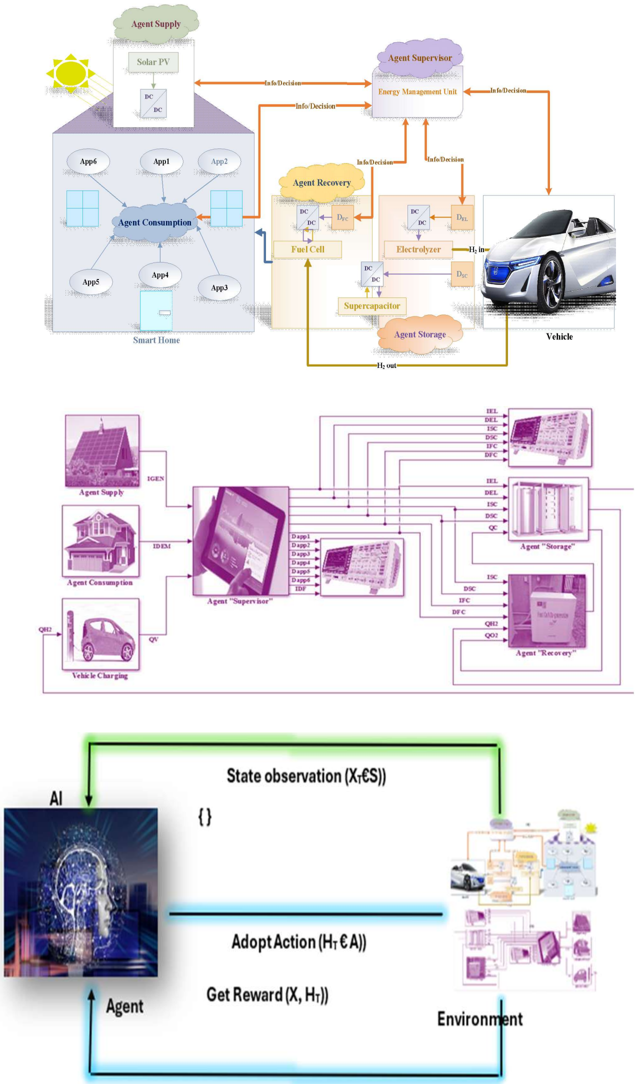

Figure 1. Autonomous Hybrid Smart Home Energy Management Architecture

Figure 1 illustrates the IHEMS framework, comprising photovoltaic systems, proton exchange mem-brane fuel cells, hydrogen refuelling, and vehicle-to-home/home-to-vehicle systems. A DDQN-based AI learning MASH manages the system, facilitating real-time energy scheduling. The MAS allows de-centralized and intelligent decision-making, with an individual agent for each energy system, storage unit and home appliance. A general description of an agent hierarchy can be a Supervisor Agent (Sink Agent): The Agent collects system state data, measures the energy flow, and manages interactions among all Agents in the architecture hierarchy. This is done to maximize the power distribution by the demand and supply situation. The eco-friendly power generation, H 2 storage, V2H communication, and AI system are enhanced by the MAS framework with DDL technology and DDQN. The agents work in a decentralized way, and the central supervisor agent optimally coordinates them; that is, it minimizes the global cost of the system and takes decisions in real time. Every agent the supervisory agent supervises is assigned a role and interacts with other agents in the MAS system. Such AI-based coordination equips with a tool to reinvigorate energy management that could autonomously develop by adapting and evolving over the system analysis from efficiency and resilience to even more com-plex forms of efficiency and resilience.

3. Problem Statement

An increasing number of smart homes utilise renewable energy sources to reduce CO2 emissions and diminish dependence on fossil fuels. Yet, providing a dependable, economical, and efficient energy source is hampered by the irregular and intermittent nature of solar electricity, changing household energy demands, and an unstable infrastructure. Contemporary energy management systems generally lack the requisite flexibility, real-time intelligence, and integrated control to handle many energy sources, including solar photovoltaics, hydrogen fuel cells, and electric vehicles within a single residence. Moreover, conventional scheduling methods may not fully use two-way V2H and H2V communication modes and lack advanced learning algorithms for autonomous control. This highlights the necessity for a cohesive, intelligent energy management system capable of proactively optimising the interplay between diverse energy sources, storage systems, and home demands, particularly in response to abrupt climatic fluctuations and load requirements. The proposed design will address this gap by developing and demonstrating an IHEMS utilising MAS and DDQN technology to optimise intelligent, scalable, real-time decisions regarding solar systems, pulsed hydrogen fuel cells, hydrogen refuelling, and V2H/H2V technologies

3.1. Agent-Based Energy Management System Design

The Integrated IHEMS is modelled after a MDP, where each agent represents a decision unit using DDL over DDQN. The system dynamically optimizes energy generation, storage, consumption, and trading decisions (See Equation 1) [21].

$$\left|\begin{array}{l}(S, A, P, R, \gamma) \\ \left\{\begin{array}{l} Q(s_t, a_t) = E[R_t + \gamma \max\limits_{a_t+1} Q(s_{t+1}, a_{t+1})] \\ \pi(a_t | s_t) = \arg\max\limits_{at} Q(s_t, a_t) : \textbf{policy} \end{array}\right.\end{array}\right.$$

In this context, S stands for system statuses, which include PV output, SOC, hydrogen levels, and the state of EV. A denotes Actions, which refer to judgements on the regulation of entities, including acti-vating or deactivating them, altering the current, and selecting a mode. P(st+1|st, at) represents the transition probabilities, which the operational mechanics of the physical system determine. R (s,t, a) represents the reward function considering efficiency, cost, and reliability, whereas γ denotes the dis-count factor for future rewards.

3.2. PV Agent

The PV power supply agent manages the system that produces electricity demand. This agent func-tions at the MPP to guarantee that the PV modules consistently produce optimal power, irrespective of variations in solar radiation levels. The agent uses DDQN-based learning to assess solar power availa-bility and choose the ideal operational point. The agent informs the supervisory agent of the present generating capacity and makes modifications based on expected environmental changes. This method enables anticipatory energy planning (see Equation 2) [22].

$$\begin{cases} P_{PV}(t)=V_{PV}(t)\cdot I_{PV}(t) \\ \begin{cases} s_t=\{\text{Irradiance}, V_{\text{PV}}, I_{\text{PV}}\} \\ a_t=\{\text{Adjust MPP voltage/current}\} \end{cases} \\ \textbf{Reward}: \textit{Maximize PV output, avoid surplus loss} \\ \textbf{Learning}: \textit{DDQN updates Q-values for MPP control policy} \end{cases}$$

3.3. Home Agent

The load depletion factor calculates residential energy consumption for heating, cooling, lighting, and charging electric vehicles. The supervisor evaluates the expected load during the load depletion period. Consumption patterns and peak periods are also examined. If this factor exists, the supervisor can enhance demand management by suggesting load shifts or establishing operational priorities. Equation 3 shows that this proposed strategy enhances system reliability and reduces costs [23].

$$\begin{cases} P_{Load}(t)=\sum_{i=1}^{n} Pappliance, i(t) \\ \textbf{State}: \textit{Appliance states, forecasted consumption.} \\ \textbf{Action}: \textit{Load shifting, priority scheduling.} \\ \textbf{Reward}: \textit{Minimize peak load, reduce grid cost.} \\ \textbf{Learning}: \textit{DDQN optimizes appliance control schedule} \end{cases}$$

3.4. Hydrogen Production Agent:

The hydrogen production factor ensures that the electrolyzer operates efficiently, converting excess solar energy into hydrogen at a high rate for long-term storage. Faraday's electrochemical law of hydrogen production (in DDQN scheduling) allows the factor to determine when and how much hydrogen to produce based on expected energy surplus, the presence of an HL array in the tanks, or anticipated demand. This proactive approach can reduce energy loss and make the system more autonomous (see Equation 4) [24].

$$\begin{cases} m_{H_2}=\dfrac{I_{el}\cdot t\cdot M_{H_2}}{n\cdot F} \\ \textbf{State}: \textit{PV surplus, H2 tank level.} \\ \textbf{Action}: \textit{Electrolyzer ON / OFF, current adjustment.} \\ \textbf{Reward}: \textit{Efficient H2 generation, avoid overfill.} \\ \textbf{Learning}: \textit{DDQN policy for production scheduling} \end{cases}$$

3.5. Hydrogen Recovery Agent:

The hydrogen recovery agent manages the operation of the PEM fuel cell and ultracapacitor storage system (USS). Its role is to recover stored hydrogen energy during solar power shortages and stabilize the system using fast-reaction supercapacitors. This agent uses a DDQN-based decision-making mechanism to determine optimal fuel cell operation periods, avoid unnecessary PEMFC cycles, ex-tend component life, and ensure continuous power supply during critical periods (See Equation 5) [25].

$$\begin{cases} m_{H_2,cons}=\dfrac{I_{PEMFC}\cdot t\cdot M_{H_2}}{n\cdot F} \\ \Delta SOC_{SC}=\dfrac{I_{SC}}{C_{SC}} * \dfrac{\Delta t}{V_{SC}} \\ \textbf{State}: \textit{H2 tank status, SOC of USS.} \\ \textbf{Action}: \textit{Activate PEMFC, adjust discharge rates.} \\ \textbf{Reward}: \textit{Maintain energy supply, prevent degradation.} \\ \textbf{Learning}: \textit{DDQN selects optimal energy recovery strategies.} \end{cases}$$

The hydrogen recovery agent oversees the functioning of the PEM fuel cell and ultracapacitor. Its function is to retrieve stored hydrogen energy during solar power deficits and to stabilise the system with rapid-response supercapacitors. This agent employs a DDQN-based decision-making framework to determine optimal operating times for the fuel cell, mitigate superfluous PEMFC cycles, prolong component longevity, and guarantee uninterrupted power delivery throughout key phases (refer to Equation 5) [25].

$$\begin{cases} P_{EV}(t)=V_{EV}(t)\cdot I_{EV}(t) \\ \textbf{State}: \textit{EV SOC, availability.} \\ \textbf{Action}: \textit{Charging / discharging decisions.} \\ \textbf{Reward}: \textit{Optimize storage use, enhance autonomy.} \\ \textbf{Learning}: \textit{DDQN learns vehicle energy management policy.} \end{cases}$$

3.7. Storage Status Agent:

The Storage Condition Agent monitors the condition of the stored energy centre (SOC) and the hydro-gen tank. This agent also oversees the pressure, charging, and discharge rates to ensure everything runs safely. The agent uses a predictive control system based on the DDL model to regulate storage usage, prevent over-discharging, and maintain optimal charging levels for the supercapacitors. The supervisor receives constant reports on the available storage capacity, enabling them to determine the operating schedule (See Equation 7) [27].

$$\begin{cases} Q_{H_2}(t) = Q_{in}(t) - Q_{out}(t) \\ \textbf{State}:\ \textit{Hydrogen tank level},\ \textit{SOC}. \end{cases} \quad \textbf{(7)}$$

3.8. Hydrogen Station Agent:

The hydrogen station agent operates the HRS, manages hydrogen production and refuelling cycles, and regulates tank pressure. Using DDQN-based predictions, this agent schedules refuelling operations, optimises hydrogen production timing, and ensures safe pressure levels in storage tanks. This agent contributes to the seamless integration of hydrogen production, storage, and consumption processes (See Equation 8) [28].

$$\begin{cases} Q_{stored} = Q_{prod} - Q_{used} + Q_{refuel} \\ \textbf{State}:\ \textit{Refueling demand},\ \textit{tank pressure}. \end{cases} \quad \textbf{(8)}$$

3.9. Supervisor agent

The supervisor agent acts as a global decision-maker, coordinating the actions of all other agents using DDQN. Its primary function is to balance energy generation, storage, and consumption in real-time while reducing operating expenses and enhancing system reliability. The supervisor constantly checks how the system is doing and chooses the best way to operate (like using only solar power or combining solar power sources). Additionally, the system supports energy storage and management for vehi-cle-to-home and home-to-vehicle applications, adjusting its decision rules based on rewards related to its performance in efficiency, cost, and stability (See Equation 9) [29].

$$\begin{cases} R(t) = \alpha \cdot \eta(t) - \beta \cdot Cop(t) - \gamma \cdot P_{grid}(t) - \delta \cdot E_{loss}(t) \\ P_{BAL}: P_{PV}(t) + P_{PEMFC}(t) + P_{EV}^{V2H}(t) + P_{ESS}(t) = P_{Load}(t) + P^{H2V}(t) + P_{grid}(t) \\ P_{BAL}: P_{PV}(t) - P_{Load}(t) \end{cases}$$

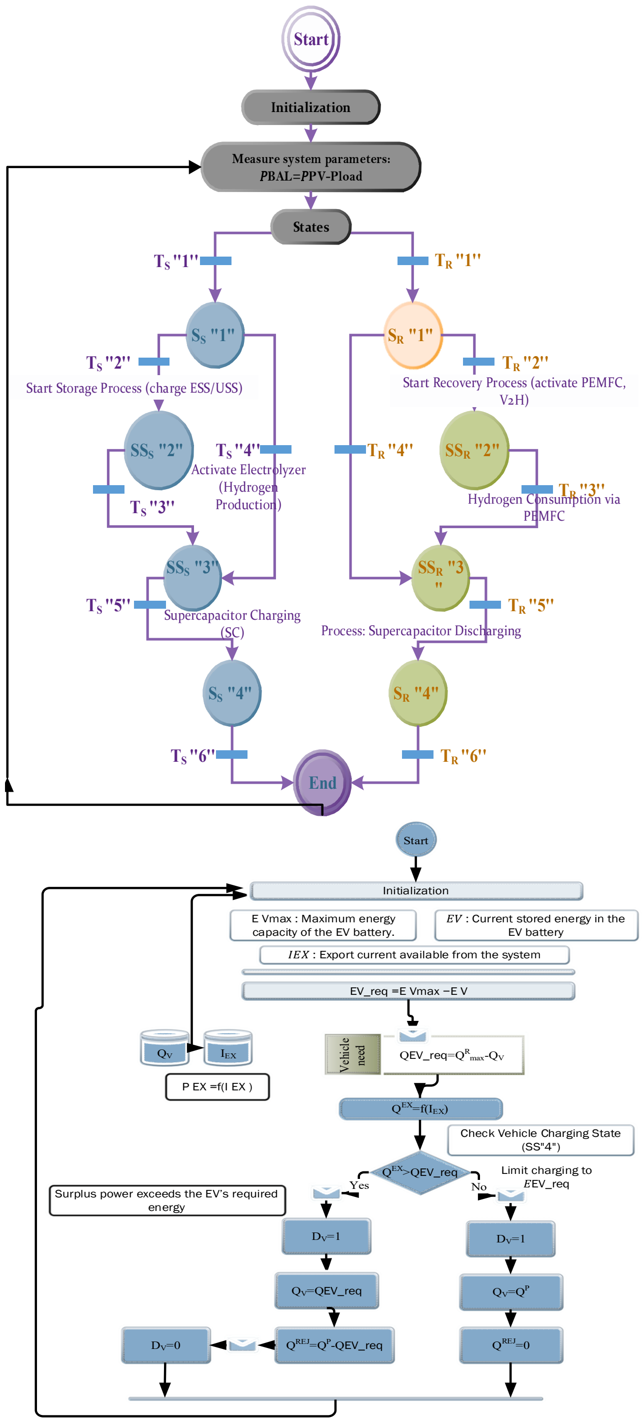

Figure 2: (a): State-Based Decision Process Using DDQN, MDP, and TS/TR Transitions; (b): Adaptive Vehicle Charging Using Export Power, Energy Requirement Calculation, and Dynamic Current Adjustment.

4. Intelligent Home Energy Management System

4.1. DDQN-based decision-making

The proposed IHEMS, which integrates MAS, DDL, DDQN, and MDP, would ensure that the renewa-ble energy generation, storage system, and residential loads could collaborate in real-time. The control strategy consists of two fundamental flowcharts: Figure 2a illustrates that the supervisor agent man-ages all these things globally. It monitors the system's status and the choices made by DDQN, coordi-nate tasks among the agents (PV, PEMFC, HRS, EV, and storage system), and adjusts learning rules using feedback and Q-value. Figure 2b illustrates each agent himself. Every agent observes its state, selects actions with the ε-greedy policy of DDQN, performs the control action (i.e., dispatch the electro-lyser or EV charging), and sends input to the supervisor. The decision-making process uses a state machine model with specific state changes (like starting storage, recovering, managing hydrogen stor-age/usage, managing supercapacitors, and loading vehicles in SS"4"). This allows the system to transi-tion energy flows dynamically and ensures that home energy management is stable and efficient.

An IHEMS work is explained by organised conditions and changes controlling energy moving between production, storage, hydrogen generation, and the grid. Those conditions are defined by some system states (SS) and some recovery states (SR). Energy balance, hydrogen levels, supercapacitor state of charge, grid availability, and TS/TR from electricity pricing represent operational parameters. These changes are summarised in Table 2, which indicates that the system banks energy, spends it when you have it, controls H_2 and supercapacitor usage, or manages grid sharing as appropriate for cost and availability. State 5 (Grid Management) and State 6 (Price-Aware Energy optimisation) increase flexi-bility, allowing for instantaneous energy market effects, which makes the system more economical and secure.

Table 2. Check Conditions and Apply TS / TR Transitions

State (SS/SR)	Transition (TS/TR)	Condition	Process Action
SS"1"	TS"1": PBAL>0	Power surplus	Start Storage Process (charge ESS/USS)
SR"1"	TR"1": PBAL<0	Power deficit	Start Recovery Process (activate PEMFC, V2H)
SS"2"	TS"2": SOCH2<1	Hydrogen tank not full	Activate Electrolyzer (Hydrogen Production)
SR"2"	TR"2": SOCH2>0	Hydrogen available	Hydrogen Consumption via PEMFC
SS"3"	TS"3": SOCH2>1	High Hydrogen level	Supercapacitor Charging (SC)
	TS"4": PBAL< INEL	Low Energy Balance, Normal Level	Supercapacitor Charging (SC)
SR"3"	TR"3": SOCH2=0	No Hydrogen left	Supercapacitor Discharging
	TR"4": PBAL< INFC	Critical Energy Deficit	Supercapacitor Discharging
SS"4"	TS"5": SOCSC>1	SC Full, Vehicle Available	Vehicle Charging (V2H Mode Priority)
SR"4"	TR"5": SOCSC=0	SC Empty	Appliance Operation Control (Load Scheduling)
SS"5"	**TS"6": Grid Availability = TRUE**	Grid power available	Import Energy from Grid (Grid-Assisted Recovery)
SS"5"	TS"6": Grid Availability = TRUE	Grid power available	Import Energy from Grid (Grid-Assisted Recovery)
SR"5"	TR"6": Grid Availability = FALSE	Grid power unavailable	Disconnect from Grid, Switch to Self-Supply
SS"6"	TS"7": Energy Price < Threshold	Low electricity price period	Charge Battery or EV from Grid (Cost Optimization)
SR"6"	TR"7": Energy Price > Threshold	High electricity price period	Avoid Grid Charging, Use Renewable/Stored Power

Algorithm 1 explains managing IHEMS using MDP and DDQN, coordinating multiple agents, applying state machine logic, and learning adaptively. The algorithm monitors hydrogen, power generation, consumption, storage, vehicle energy equipment, GSO, and energy pricing. It then determines the op-timal energy use: storing it, recovering it, generating hydrogen, charging the vehicle at home, doing laundry, running the dishwasher, or postponing these tasks. The result is an electronic system designed for continuous power conditions (SS/SR with TS/TR logic) that provides real-time learning perfor-mance feedback, ensuring optimal energy use, low costs, and reliable operation in homes striving for smart home designs.

Algorithm 1: Unified Algorithm for IHEMS

1 Initialize system parameters:
PPV, Pload, SOCH2, SOCSC, EV, EVmax, Grid Status, Energy Price), DDQN networks, replay buffer, learning rates, and define agents (Supply, Consumption, Storage, Recovery, Hydrogen Station, V2H/H2V, Supervisor).

2 Loop while system is active:
Measure power balance: PBAL = PPV - Pload
Supervisor collects current state: St = {PBAL, SOCH2, SOC_SC, EV, Grid Status, Energy Price, AppStatus}

3 IF PBAL > 0 THEN
Set State = SS"1", apply TS"1", start Storage Process (charge ESS/USS)
ELSE IF PBAL < 0 THEN
Set State = SR"1", apply TR"1", start Recovery Process (activate PEMFC, V2H)
END IF

4 IF SOCH2 < 1 THEN
Set State = SS"2", apply TS"2", activate Electrolyzer for Hydrogen Production
ELSE IF SOCH2 > 0 THEN
Set State = SR"2", apply TR"2", consume Hydrogen via PEMFC
END IF SOCH2 > 1 OR P_BAL < I_NEL THEN
Set State = SS"3", apply TS"3"/TS"4", charge Supercapacitor
ELSE IF SOCH2 = 0 OR PBAL < I_NFC THEN
Set State = SR"3", apply TR"3"/TR"4", discharge Supercapacitor
END IF
IF SOCSC > 1 THEN
Set State = SS"4", apply TS"5", prioritize Vehicle Charging (V2H)
ELSE IF SOCSC = 0 THEN
Set State = SR"4", apply TR"5", enter Appliance Load Scheduling Mode
END IF
IF Grid Status = TRUE THEN
Set State = SS"5", apply TS"6", enable Grid-Assisted Recovery
ELSE
Set State = SR"5", apply TR"6", operate in Self-Supply Mode
END IF
IF Energy Price < Threshold THEN
Set State = SS"6", apply TS"7", optimize cost by charging EV/Battery from Grid
ELSE
Set State = SR"6", apply TR"7", avoid Grid Charging, use Renewable/Stored Power
END IF
IF State = SR"4" THEN
Set active home appliances
Check deficit and recovery rate via Recovery Agent
WHILE PBAL < 0:
Turn OFF non-critical appliances based on priority
END WHILE
END IF
Supervisor selects optimal action at = argmax Q(st, at) using DDQN policy
Execute selected action through the corresponding agent
Compute reward:
Store experience (st, at, rt, s{t+1}) in replay buffer
Update Q-values:

Periodically update target Q-network
Continue to the next monitoring cycle
END LOOP.

3.2. DDQN Neural Network Input-Output Configuration for IHEMS

The proposed DDQN-based learning architecture for IHEMS aims to map environmental system states with optimal control actions accurately.

Table 3. DDQN Neural Network Configuration for IHEMS

Layer	**Neurons**	**Description**	**Activation Function**
Input Layer	7	**System states:** P_{BAl}, SoC_{H2}, SOCSC, E_V, Grid Status, Energy Price, Appliance Status	
Hidden Layer 1	64	Nonlinear feature extraction	ReLU
Hidden Layer 2	64	Nonlinear feature extraction	ReLU
Output Layer	8	**Control actions :** Appliance scheduling, electrolyzer ON/OFF, PEMFC ON/OFF, V2H/H2V mode, grid interaction, SC management	Linear

The input layer of the Neural Network (NN) includes system state-related properties, such as BAL, hydrogen tank SOCH2, SOCSC, VV (representing the battery level of the electric vehicle), grid availability, energy pricing, and device status. These observations allow the agent to perceive and understand the system's current state. A matrix of potential actions is generated in the output lay-er, covering actions such as controlling devices, operating the electrolyzer, activating the PEMFC, exchanging V2H or H2V, charging/discharging the supercapacitor, and using or not using the grid. Table 3 illustrates the network architecture, which includes the number of neurons in each layer. The number of neurons in the input layer corresponds to the seven crucial system state variables. Two hidden layers (64 neurons in each layer) with ReLU activation functions capture the nonlin-ear relationship between inputs and outputs.

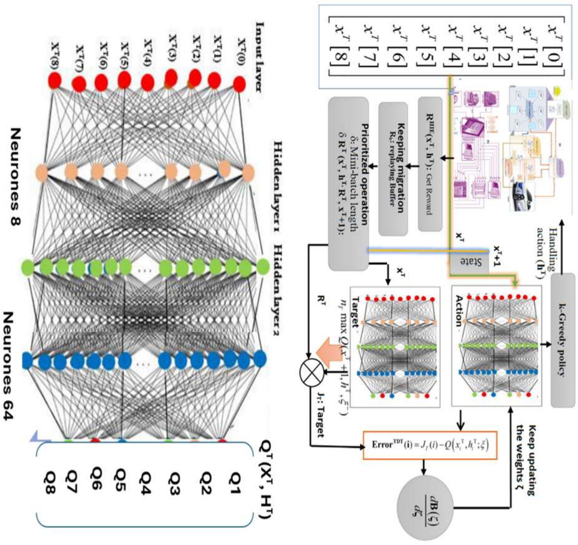

Figure 3. Double-DQN-Based Intelligent Energy Management Framework for IHEMS.

The output layer includes neurons for the eight possible actions. Table 8 illustrates the DDQN network for the IHEMS. The architecture consists of seven input neu-rons representing the state, two hidden layers for processing, and eight in the out-put layer to perform power management actions. Figure 3: Functionality of the Double DQN-based control technology with the IHEMS. This approach involves continuous monitoring of system operating conditions, using a deep learning algo-rithm to determine the best actions, and adaptive control of power flows to con-serve resources and ensure their stability and optimal utilization.

5. Obtained Results

This section covers the findings from the modelling and validation of the recently created IHEMS, which combines PV, PEMFC, HRS, and V2H/H2V with the help of DDQN-based control. The findings indicate that the proposed control al-gorithms facilitate adaptive energy management, optimise hydrogen utilisation, enhance household self-sufficiency, reduce grid dependence, and yield financial benefits by utilising genuine Tunisian meteorological data through MATLAB/Simulink. The findings demonstrate that the suggested DDQN-enhanced multi-agent system for smart home energy management is stable and capable of real-time responsiveness.

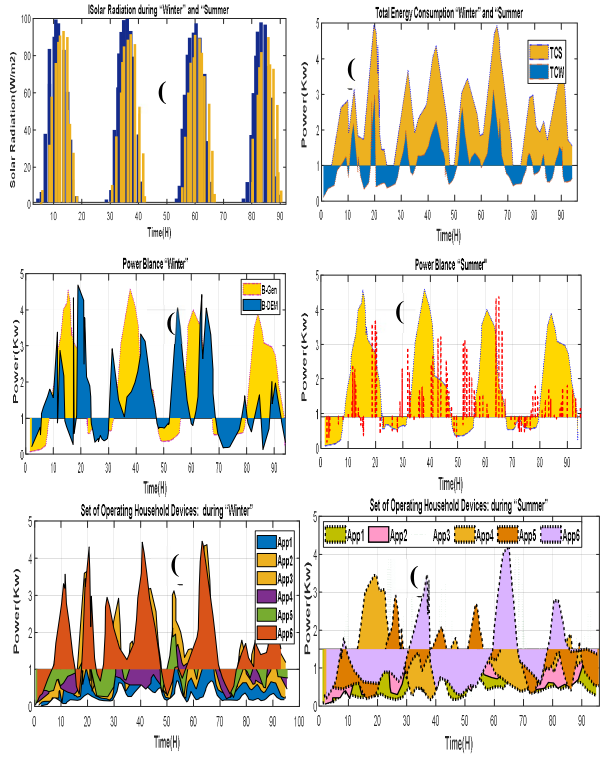

Figure 4. Input Simulation Parameters: (a) Solar Radiation; (b) Total energy demand (TED); (c) Seasonal Power Balance Analysis.

5.1. Simulation setup and parameters

The validity of the proposed IHEMS was tested using actual meteorological data from Tunisia using simulations with MATLAB/Simulink. The input consists of four consec-utive days in winter and summer of solar irradiance, temperature and residential en-ergy use histories. This technique allows you to test the system in real-life environ-ments that may change.

Table 4. Daily Energy Flow Metrics under Tunisian Seasonal Conditions

Day	Generation Avg (A)	Consumption Avg (A)	H_2 Produced (mol)	H_2 Consumed (mol)	SC Charging (A)	SC Discharging (A)
Winter (Day 1)	12.3	14.2	6.20e-04	4.20e-05	5.2	3.1
Winter (Day 2)	13.1	16.0	6.75e-04	6.70e-05	8.1	13.4
Winter	12.8	17.4	6.15e-04	9.50e-05	6.5	12.1

(Day 3)						
Winter (Day 4)	11.9	13.5	5.95e-04	5.80e-05	5.7	7.6
Summer (Day 1)	14.6	15.1	6.90e-04	6.20e-05	9.2	9.5
Summer (Day 2)	14.8	15.4	6.88e-04	6.40e-05	8.8	7.8
Summer (Day 3)	14.1	15.3	6.70e-04	6.35e-05	8.4	4.2
Summer (Day 4)	13.9	15.2	6.65e-04	6.30e-05	7.9	3.5

The main input factors include daily household usage patterns and solar information, such as brightness and temperature, taken from experimental data in Tunisia (see Figure 4a). Figure 4a illustrates the solar values for the daily seasonal trends during winter and summer based on data from Tunisia's weather. As anticipated, insolation levels are significantly greater throughout the summer, signifying enhanced photovoltaic generation capability. The seasonal transition substan-tially influences the energy availability for houses and storage systems. Figure 4b illustrates the total energy consumption of all homes. The observed variations revealed that winter demand, in particular, frequently surpassed the capacity to generate power. This figure illustrates the signifi-cance of storage techniques and efficient load planning in averting supply problems. Figure 4c illustrates the calculated power balance (PBAL), which delineates the disparity between energy used and produced throughout the simulation. Positive PBAL readings during the summer signify a surplus of electricity, indicating excessive grid stability. Winter evaluations are negative, showing significant progress without a hydrogen infrastructure and the necessary innovative control sys-tems." Figure 4.d illustrates that individuals use greater energy at home throughout winter. People need to heat their homes and use certain appliances more frequently. The heightened demand for energy and the restricted availability of sunshine underscores the imperative to regulate energy use and incorporate hydrogen energy storage into a residential energy management system.

5.2. Energy flow management behaviour

To analyze the dynamic operation of IHEMS, this section examines how power is coordinated between PV generation, PEMFC, hydrogen storage, and EVs using bidirectional V2H and H2V capabilities. Using DDQN learning within a MDP, the supervisory agent manages all state transi-tions (SS/SR) and conditions (TS/TR), as shown in Table 5.

State	Transition	Condition	Action
SS1	TS1	$P_{BAL} > 0$	Start energy storage (ESS/USS)
SR1	TR1	$P_{BAL} < 0$	Activate recovery (PEMFC or V2H)
SS2	TS2	$SOC_{H_2} < 1$	Produce hydrogen (activate electrolyzer)
SR2	TR2	$SOC_{H_2} > 0$	Consume hydrogen via PEMFC
SS3	TS3/TS4	$SOC_{H_2} > 1$ or $P_{BAL} < IN_{EL}$	Charge supercapacitor (SC)
SR3	TR3/TR4	$SOC_{H_2} = 0$ or $P_{BAL} < IN_{FC}$	Discharge supercapacitor
SS4	TS5	$SOC_{SC} > 1$	Charge EV (V2H mode)
SR4	TR5	$SOC_{SC} = 0$	Load scheduling (appliance management)
SS5	TS6	Grid available	Import energy from grid
SR5	TR6	Grid unavailable	Switch to self-supply mode
SS6	TS7	Energy price < Threshold	Grid charging for EV/battery (cost-efficient)
SR6	TR7	Energy price > Threshold	Use stored/renewable power, avoid grid use

Figure 5. a shows PV generation versus household demand over 24 hours. The overlap shows pe-riods of excess power (midday) and shortages (early morning and evening), which form the basis for storage and recovery operations. ESS and USS are switched on when excess power is detected. This sub-figure illustrates the charging cycles, particularly during periods of excess PV power in the middle of the day, allowing for later discharge during peak demand. Hydrogen production by electrolysis begins when excess PV power exceeds the electrolysis system's capacity. This diagram shows the periods when the electrolyser is active, converting excess electricity into hydrogen for later use by the PEMFC unit. Indeed, it illustrates recovery events using PEM fuel cells, SC, and V2H discharges. These resources are activated during high-demand periods, helping maintain en-ergy balance and reduce reliance on the grid. When demand exceeds production (SR1, TR1), the PEMFC unit is activated to convert the stored hydrogen into electricity (SR2, TR2). The hydrogen recovery agent also monitors the ultracapacitor discharges (SR3, TR3, TR4) to quickly respond to load changes.

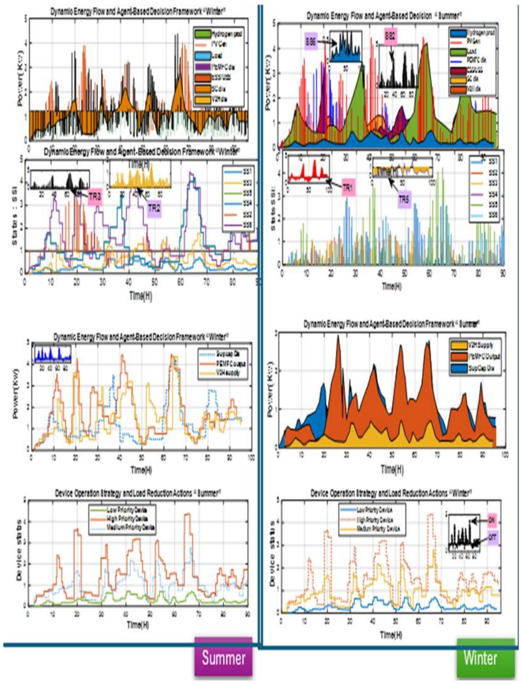

Figure 5. Overview of the 24-hour power flow in an Electricity IHEMS; (a): Charging behaviour of energy storage systems (ESS/USS); (b): State transition mechanism of a smart home energy man-agement system (IHEMS) (SS/TR table visualization); (c): Dynamic Energy Flow and Multi-Agent Decision-Making Mechanism (d): Appliance Operation Strategy and Load Reduction Procedures: Peak Demand Discharges.

Figure 5.b shows the IHEMS's state space representation in a state transition diagram. The system switches between operational modes (such as store, recover, produce, and dispose of) based on spe-cific rules (PBAL, SOCH2, SOCSC) and a DQN policy from a Markov decision process—figure 5c shows how well the DDQN method works to manage real-time energy units, such as PV, BT hydro-gen storage (as a backup), EVs, and domestic appliances. The energy routing path changes based on the system's state and the signals from the grid. This shows that the structure of the entity makes wise choices.

Figure 5.d shows how much power the PEMFC, SC, and V2H cells can give off when the system needs the most power. It shows how to intelligently regulate different energy flows to stabilise the system and avoid overloading or relying on expensive utility power. The graph shows how much energy domestic appliances like washing machines, dishwashers, and electric vehicle chargers use during the day. The officials in the basement decide how many appliances to run de-pending on load forecasts, energy price indications, and the status of charge (SOC). When there isn't enough power, we turn off non-essential loads and turn on all activated appliances simultaneously.

5.3. Adaptive Energy Management, Hydrogen Utilization, and V2H Exchange for Grid-Independent Smart Homes

This section illustrates the dynamic operation of an IHEMS, demonstrating its abil-ity to adaptively manage photovoltaic power generation, hydrogen production and consumption, vehicle/vehicle interactions, and smart device scheduling. It evaluates system stability under varying energy demands, efficient vehicle-to-home integra-tion, and strategies for reducing grid dependency and lowering energy costs. Each subfigure provides insight into different operational aspects, including real-time power flow, agent-based state transitions, energy loss during peak load periods, and specific device control under limited power conditions.

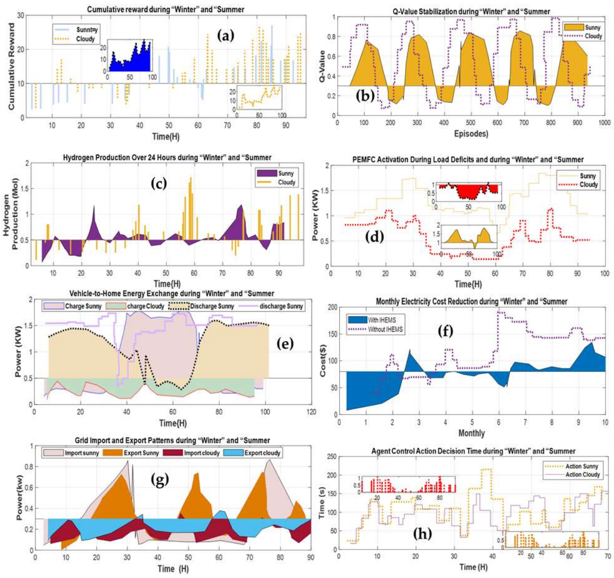

Figure 6. Performance Evaluation and Intelligent Decision-Making in IHEMS: (a): DDQN Reward Convergence; (b): Q-Value Stabilization; (c): Hydrogen Production Over 24 Hours; (d): PEMFC Ac-tivation During Load Deficits; (e): Vehicle-to-Home Energy Exchange; (f): Monthly Electricity Cost Reduction; (g): Grid Import and Export Patterns; (h): Agent Control Action Decision Time.

5.3.1. System stability, adaptation and evaluation of hydrogen management

Figure 6 shows the results of a detailed study of how the IHEMS system performs with hydrogen, focusing on its effectiveness. Figure 6a shows that the cumulative rewards of the DDQN operator converge over iterations. The system is self-adaptive, learning from past errors to optimize control strategies for efficiency and energy efficiency. Figure 6b shows the curve at which the Q value reaches a plateau. This pattern indicates that the operator's performance will improve and achieve greater consistency over time. Figure 6c shows that the electrolyzer produces the most tremendous amount of hydrogen when receiving additional solar energy, meaning that hydrogen production directly depends on the en-ergy it receives, especially at 52°C (TS2). This figure demonstrates the ability to store excess re-newable energy for long periods. Figure 6d shows the effect of the hydrogen tank state of charge (SOC) on the PEMFC operating frequency during active and inactive states. Additionally, the figure shows that the PEMFC operates continuously in SR1 and SR2 to produce electricity when generators are insufficient, improving system reliability. The results indicate that the IHEMS can effectively align energy requirements with fluctuating solar and electricity prices while efficiently overseeing hydrogen generation, storage, and use.

5.3.2. Vehicle-to-Home Energy Exchange Evaluation

This section analyzes the role of electric vehicles in IHEMS, focusing on H2V in-teractions. Figure 6.e shows the variation of electric vehicle charging patterns throughout the day, depending on energy availability and demand. The controller initiates the power discharge from the vehicle to the home. The controller charges the electric vehicle during periods of high demand and when surplus or low-cost energy is available. This bidirectional power flow enhances the system's adaptabil-ity and maintains the home's energy balance. It also facilitates off-peak charging of electric vehicles, resulting in cost and space savings.

5.3.3. Optimizing energy costs and reducing grid dependency

The proposed IHEMS reduces residential electricity consumption and enhances resilience to power interruptions. Figure 6f illustrates the alterations in the monthly electricity bill resulting from the IHEMS system. The strategy conserves substantial funds by maximising the use of renewable energy, emphasising energy storage, and charging electric vehicles during off-peak rates. The grid's functions in product import and export are illustrated in Figure 6 If the system generates surplus solar electricity, it transmits the excess power to other locations. This be-haviour indicates enhanced procedural efficiency, which results in reduced import requirements.
To gauge their magnitude, we examined various scenarios involving electric vehi-cles and enhanced hydrogen storage. The system continued to function, and the agents persisted in collaborating despite the ineffectiveness of their cooperation agreements. Figure 6.g illustrates each agent's decisions in real-time to determine their control actions within about 200 milliseconds. The IHEMS architecture ef-fectively facilitates several agents' real-time coordination and synchronisation amid rapid changes. Table 6 presents the primary performance metrics: the self-sufficiency rate, average monthly network import reduction, and accrued fi-nancial savings.

Table 6 : summarizes key performance metrics : self-sufficiency ratio, average monthly grid im-port reduction, and cost savings
.

Metric	Without IHEMS	With IHEMS	Improvement (%)
Average Monthly Cost (SAR)	510	365	28.43%
Self-Sufficiency Ratio (%)	62	84	+22%
Grid Import (kWh/month)	820	460	-43.90%

5.4. Discussion

The simulation results indicate that the proposed IHEMS will operate as expected. It uses hydrogen energy technology, bidirectional electric vehicle energy flow, and online decision-making combined with MAS and DDQN. The IHEMS adopts an MDP-based control approach for handling the chal-lenges associated with unpredictable home loads, the non-availability of local renewable energy sources, and dependence on the grid. Storing hydrogen with PEMFC We can "store" surplus power by controlling the electrolyser's and the PEMFC's activities, which we can retrieve if needed. At times, the production of hydrogen fluctuates between excessive and insufficient levels. V2H/H2V operations are present on the device used for covert service. These electric cars respond to the price of electricity or the grid's condition in terms of demand levels. Play for a while, and you should notice rewards and Q-values cumulating towards each other. This is how the agents find the action plan. Such learning can easily adapt to environmental changes, including load, solar radiation, power demand patterns, or a new tariff schedule. The price decreased by 28.43% with IHEMS, and 22% of incidents were cared for at home. And that's good for business and operations. Results The modelling— which con-sidered hydrogen storage and electric vehicles – suggested it could work well at scale. (8) is particular-ly appealing in practice, where the agents may have as low as 200 milliseconds per shot to decide. This means that the technique we recently discovered can be utilised in normal smart homes to ef-fectively and swiftly control energy. This paper proposes a unique system for managing energy in smart homes that integrates hydrogen technology, DDQN-based decision-making, and multi-agent coordination.

6. Conclusion and future work

This work specifics the outlines, implementation, testing, and experimental results of the IHEMS, which is based on MAS and DDQN learning within a MDP framework. The focus is on the IHEMS framework that integrates solar photovoltaic technology, kilowatt-hour storage utilising hydrogen, and EVs in a V2H/H2V context. The com-parative MATLAB/Simulink simulations demonstrate that the proposed model can operate in real-time, effectively regulate power usage, and utilise meteorological data from Tunisia for decision-making. Energy independence, hydrogen storage, and op-erational costs were all significantly diminished. The DDQN controller revised sta-tuses based on the observed energy consumption of system components. The sys-tem's reliance on the grid diminished, and its disturbance response was enhanced due to price-based strategies and bidirectional plug-in electric automobiles. We will per-form a real-time hardware-in-the-loop experiment of the IHEMS to validate our sim-ulation results. We are considering developing a system to manage the energy of an entire neighbourhood or cluster of residences. This recent report leverages blockchain to provide transparent and secure consumer energy transactions. Shortly, we intend to incorporate additional renewable energy sources, such as wind energy, to enhance the reliability and sustainability of its operation. We will employ cutting-edge fore-casting to improve the precision of our scheduling, alongside artificial intelligence, to anticipate maintenance requirements for hydrogen and storage system components.

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