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Synergy of artificial intelligence and internet of things in optimal water and energy management in smart homes: a review of physical-cyber changes, reinforcement algorithms, and economic-environmental implications

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ABSTRACT

The residential sector, accounting for approximately 20–40% of global energy consumption, represents a strategic focal point for research on energy efficiency and sustainability. The synergistic integration of the Internet of Things (IoT) and Artificial Intelligence (AI) within Cyber-Physical Systems (CPS) has opened new horizons for the integrated management of water and energy resources. Adopting a systematic review approach, this study investigates the role of CPS-based architectures, forecasting and optimization algorithms—particularly Reinforcement Learning (RL) and Deep Reinforcement Learning (DRL)—in smart homes. The findings indicate that the application of metaheuristic algorithms such as Harris Hawks Optimization (HHO) and Wild Horse Optimization (WHO), combined with fuzzy programming and the Conditional Value at Risk (CVaR) risk management criterion, can reduce household energy costs by up to 53% while maintaining computational efficiency suitable for real-time . Implementation (under 60 seconds). Nevertheless, the practical integration of these systems faces fundamental challenges, including protocol heterogeneity, infrastructure costs, cybersecurity vulnerabilities, and the absence of comprehensive frameworks for the simultaneous management of water and energy. By examining the technical, economic, and environmental dimensions of this field, the article outlines a future vision for the development of scalable and context-aware systems for next-generation smart homes.

Keywords: Smart home, Internet of Things, Artificial Intelligence, Cyber-Physical Systems, Reinforcement Learning, Energy Management, Water Management, Stochastic Programming, Cybersecurity.

1- INTRODUCTION

The building sector, as one of the largest consumers of energy and water resources, plays a pivotal role in global sustainability efforts. Estimates indicate that residential and commercial buildings in the United States account for approximately 40% of total primary energy consumption and nearly 75% of electricity consumption [1]. This substantial dependence, coupled with population growth, climate change, and rising living standards, has intensified the need for a fundamental reconsideration of household-scale resource management strategies [2, 3]

In this context, the concepts of smart homes and Home Energy Management Systems (HEMS) have emerged as key solutions for facilitating the transition toward a more . sustainable future [4]. Two enabling technologies driving this transformation are the Internet of Things (IoT) and Artificial Intelligence (AI). IoT provides the infrastructure for connecting a vast number of sensors, smart meters, and controllable devices, thereby enabling real-time monitoring and high-resolution data acquisition [5]. In parallel, AI employs advanced machine learning and deep learning algorithms to analyze these large-scale datasets, forecast consumer behavior and renewable energy generation, and make optimal, adaptive decisions [6]

Despite remarkable progress in this field, recent systematic reviews reveal that the majority of existing studies have primarily focused on the optimization of a single resource—predominantly energy—while paying comparatively limited attention to the synergy and complex interactions between water and energy within an integrated management framework [7]. Furthermore, a significant gap persists between sophisticated algorithms developed in simulation environments and their practical, scalable implementation in real-world smart homes [8]. Accordingly, this review aims to provide a comprehensive and in-depth examination of the theoretical foundations, practical applications, challenges, and future prospects of integrating Artificial Intelligence and the Internet of Things for coordinated water and energy management in smart homes, with particular emphasis on Cyber-Physical System frameworks, Reinforcement Learning algorithms, and the analysisof the economic and environmental implications.

2- ARCHITECTURE OF SMART HOME RESOURCE MANAGEMENT SYSTEMS

The Cyber - Physical Systems Approach

Modern water and energy management systems in smart homes are designed based on the architecture of Cyber-Physical Systems (CPS), which enables the integration of computational and communication processes with physical processes [9]. This architecture consists of three primary and interconnected layers [10]:

1. Physical Layer: Comprises a collection of sensors (temperature, humidity, water flow, and light intensity), smart electricity and water meters, renewable energy generation sources (solar photovoltaic panels and small-scale wind turbines), energy storage systems (batteries), and controllable household appliances.
2. Communication Layer: This layer facilitates real-time data exchange between the physical layer and the processing layer through various communication protocols, including Wi-Fi, ZigBee, Z-Wave, and cellular networks [11]. The selection of an appropriate communication protocol plays a critical role in ensuring system efficiency, security, and interoperability.

Processing and Decision-Making Layer: Serving as the intelligence core of the system, this layer incorporates Artificial Intelligence algorithms for forecasting, optimization, and control. It can be implemented either centrally through Cloud Computing or in a decentralized manner with lower latency using Edge Computing devices [12].

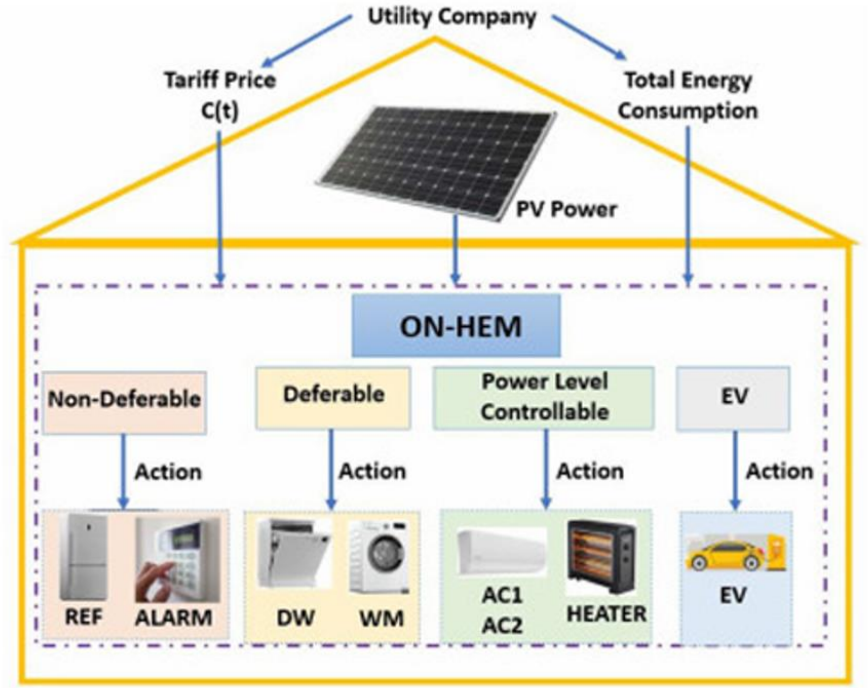

Figure 1- Architecture of the proposed online home energy management system [9]

3- APPLICATIONS OF ARTIFICIAL INTELLIGENCE AND THE INTERNET OF THINGS IN WATER AND ENERGY MANAGEMENT

Energy Generation and Consumption Forecasting

Accurate forecasting of renewable energy generation—particularly solar power, which is subject to weather-related uncertainties—as well as consumer demand constitutes one of the fundamental pillars of efficient energy management [13]. This objective is achieved by utilizing historical and real-time data collected through the Internet of Things and applying advanced machine learning models such as Deep Neural Networks (DNNs), Long Short-Term Memory (LSTM) networks, and Transformer architectures [14]

Consumption Optimization and Demand Response

Optimization algorithms, particularly those based on Reinforcement Learning (RL) and Deep Reinforcement Learning (DRL), are employed to identify optimal control policies in dynamic environments characterized by significant uncertainty [15]. These algorithms consider factors such as Real-Time Pricing (RTP), Day-Ahead Pricing (DAP), battery state of charge, solar energy generation, and user comfort levels to determine the optimal scheduling of household appliances—especially shiftable loads such as washing machines—as well as heating, ventilation, air-conditioning (HVAC) systems and electric vehicle charging processes [16]

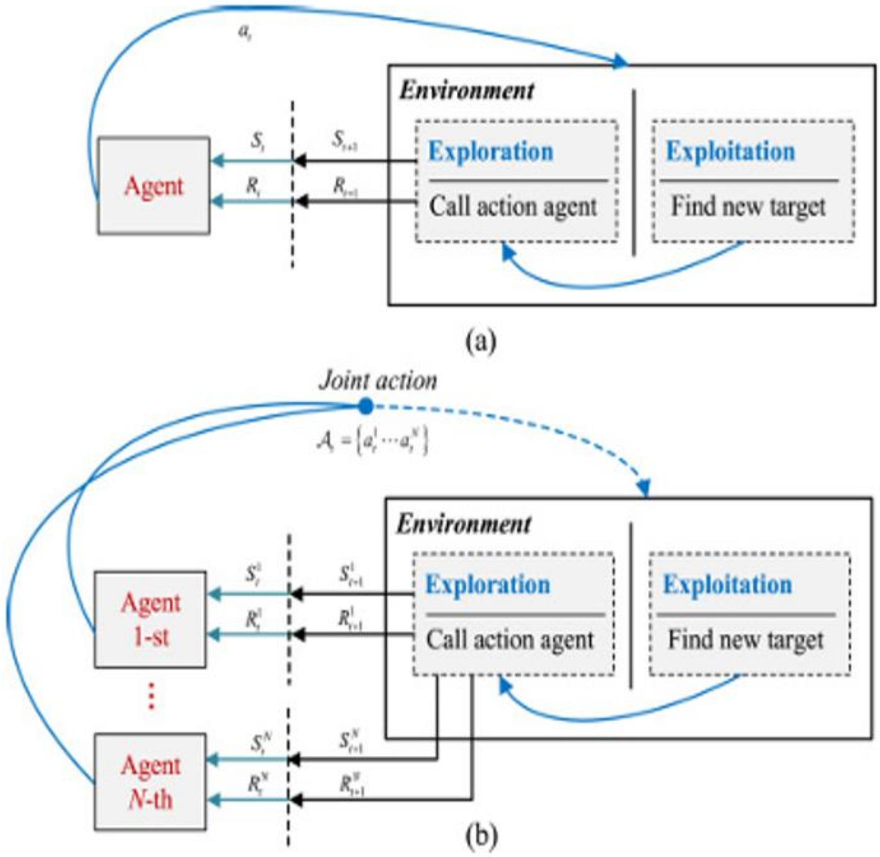

Figure 2- The RL agent interacting with the environment: (a) single-agent and (b) multi-agent RL-based algorithms [1]

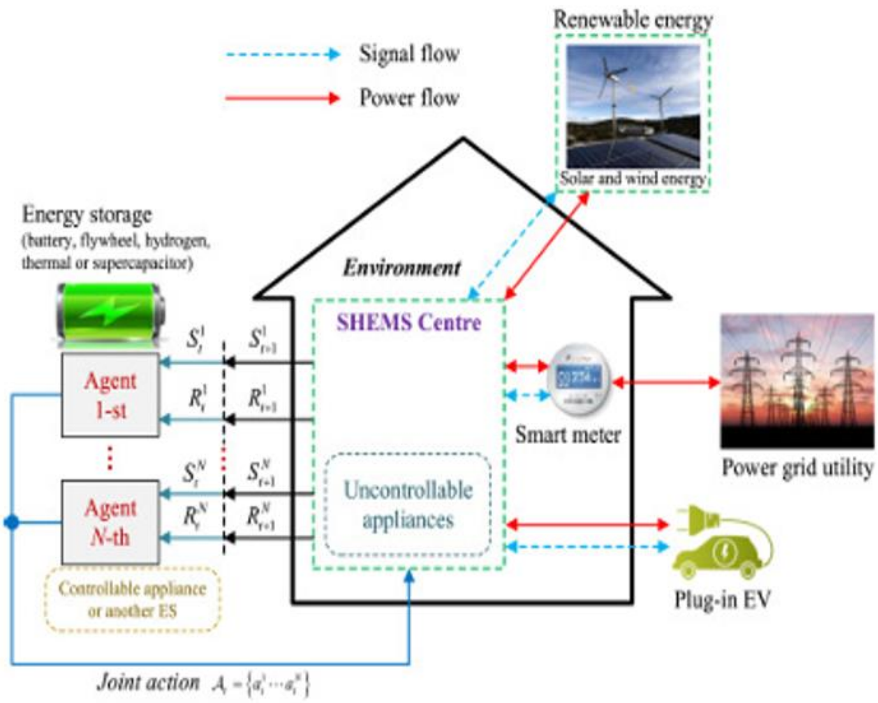

Figure 3- Smart-home energy management with energy storage using multi-agent reinforcement learning [1]

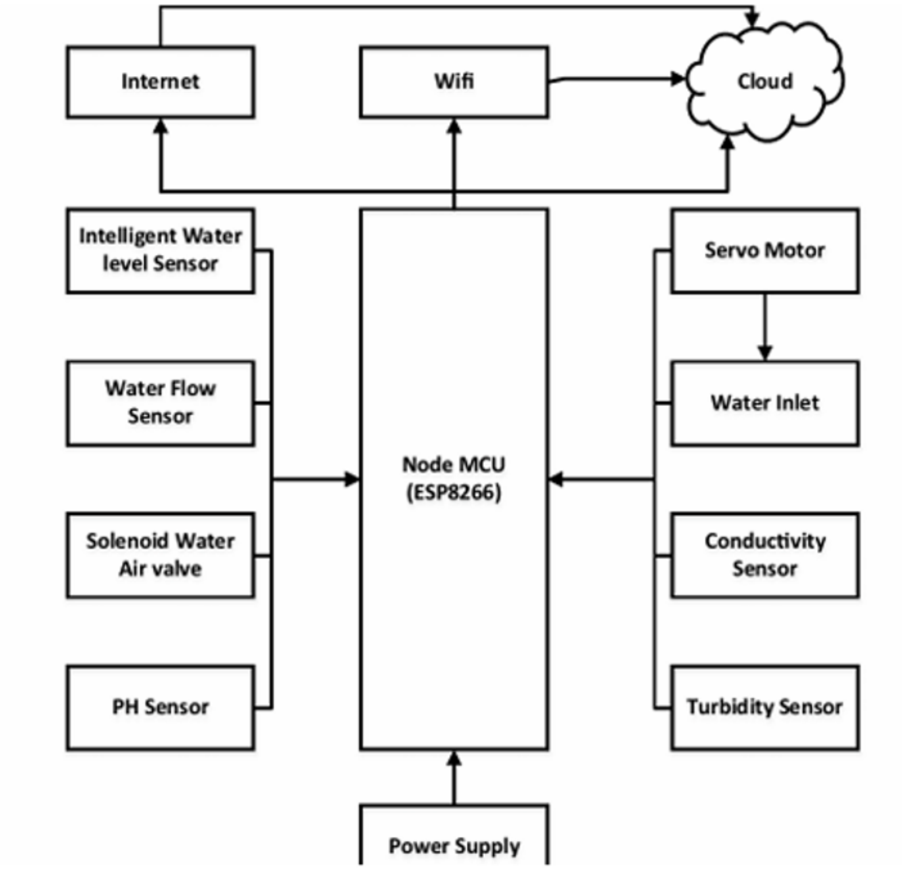

Figure 4 -Block diagram of a smart water distribution and management system, including water-level, flow, pH, conductivity and turbidity sensing, actuator control [10]

Integration of Renewable Energy Sources and Electric Vehicles

The Internet of Things and Artificial Intelligence provide the technological foundation for the intelligent integration of hybrid renewable energy systems, including solar generation, wind power, and energy storage technologies. Within this framework, Electric Vehicles (EVs) function not merely as electrical loads but also as mobile energy storage resources through bidirectional technologies such as Vehicle-to-Grid (V2G) and Vehicle-to-Home (V2H) [17]. Intelligent coordination of these resources, particularly during peak demand periods, can substantially reduce operational costs while enhancing the stability and reliability of the power grid.

Smart Water Management

Although energy management has remained the primary focus of existing research, smart water management in smart homes is rapidly gaining increasing attention. Internet of Things sensors are employed to monitor water flow, pressure, quality, and leakage detection. Integrating these data with Artificial Intelligence algorithms can facilitate water demand forecasting, consumption anomaly detection, and the optimization of smart irrigation systems and water heaters [18]. Experimental studies, such as the NexusHaus project, have demonstrated that

Integrated Thermal Energy Rainwater Storage Systems (ITHERST) can reduce peak cooling loads by approximately 75–80% [19].

Table 1- Summary of the Performance and Technical Characteristics of Key Methods Used in Smart Home Energy Management Systems

Method / Algorithm	Primary Application	Advantages	Limitations / Challenges	Reference
Mixed-Integer Linear Programming (MILP)	Optimization of appliance and energy resource scheduling	High accuracy; guaranteed convergence	Requires an accurate system model; suitable mainly for small- to medium-scale optimization problems	[20]
Metaheuristic Algorithms (HHO, WHO)	Simultaneous multi-objective optimization	Global search capability; high flexibility	Possible convergence to local optima; variable execution time	[21]
Reinforcement Learning (RL) and Deep Reinforcement Learning (DRL)	Adaptive decision-making in dynamic environments	Model-free learning; highly effective under uncertainty	Requires extensive training data; training stability challenges	[15]
Fuzzy Programming	Management of uncertainty in data and constraints	Simplifies uncertainty modeling; highly interpretable	Membership function design may depend on expert knowledge	[22]
Conditional Value at Risk (CVaR)	Risk management and cost fluctuation mitigation	Simplifies uncertainty modeling; highly interpretable	Increased computational complexity; requires scenario generation	[21]

Benefits and Implementation Challenges

Benefits

• Improved Efficiency and Cost Reduction: Experimental and simulation-based studies indicate that the application of advanced optimization algorithms in Home Energy Management Systems (HEMS) can reduce household energy costs by approximately 53% [21]. These savings are primarily achieved through direct energy conservation and load shifting to off-peak pricing periods.

• Reduction of Greenhouse Gas Emissions: Optimizing energy consumption and increasing the self-consumption of renewable energy sources significantly reduces the carbon footprint of residential buildings [23].

• Enhanced User Comfort and Interactivity: By automating operational processes and providing users with real-time feedback (e.g., energy-saving notifications), smart systems not only improve occupant comfort but also promote awareness and encourage more sustainable behavioral patterns [24].

Challenges and Barriers

• Infrastructure Costs and Integration Complexity: The initial investment required for equipping homes with IoT infrastructure and energy storage systems remains one of the principal barriers to widespread adoption. Furthermore, the heterogeneity of communication protocols and software platforms complicates the seamless integration of diverse system components [25].

• Cybersecurity and Privacy: The collection and exchange of vast amounts of sensitive personal data and behavioral information make these systems attractive targets for cyberattacks while raising serious privacy concerns [26]. Consequently, research has increasingly focused on security-oriented solutions, including blockchain technology and federated learning.

• The Simulation-to-Real (Sim-to-Real) Gap: Many advanced algorithms have been validated only under idealized simulation environments. However, their practical deployment is challenged by real-world issues such as communication latency, sensor data noise, and unpredictable user behavior [8].

Economic Analysis and Environmental Implications

Economic Benefits

From an economic perspective, the Return on Investment (ROI) of smart home systems is primarily achieved through reductions in electricity and water utility bills, together with the intelligent utilization of dynamic electricity pricing schemes (RTP and DAP) [27]. Moreover, Home Energy Management Systems can generate additional household income by exporting surplus electricity produced by rooftop photovoltaic systems to the power grid. Nevertheless, an accurate ROI assessment depends on several factors, including energy prices, discount rates, system size, and household consumption patterns.

Environmental Impacts

The principal mechanisms contributing to environmental impact mitigation include the following [23]:

1. Increasing the Share of Renewable Energy Sources: Predictive management systems enable the maximum utilization of solar and wind energy resources.
2. Reducing Overall Energy Consumption and Peak Load: Consumption optimization and demand response strategies not only decrease total energy usage but also alleviate grid stress during peak demand periods and prevents the operation of peak-load power plants, which are predominantly powered by fossil fuels.
3. Sustainable Water Management: Smart systems contribute to the conservation of this vital resource by minimizing water losses and optimizing water consumption in irrigation and heating applications.

Table 2- Comparison of the Key Economic and Environmental Benefits of Smart Home Systems

Reference	Performance Indicator	Reported Improvement	Reference
Economic	Reduction in energy costs	Up to 53%	[21]
Economic	Reduction in energy costs	Up to 30% (estimated)	[18]
Environmental	Reduction in CO_2 emissions	Up to 61%	[23]
Environmental	Improvement in energy system efficiency	Up to 72.3%	[21]
Environmental	Increased utilization of renewable energy	Significant increase in self - consumption	[17]
Reference	Performance Indicator	Reported Improvement	Reference
Economic	Reduction in energy costs	Up to 53%	[21]
Economic	Reduction in energy costs	Up to 30% (estimated)	[18]
Environmental	Reduction in CO_2 emissions	Up to 61%	[23]

4- RESULTS

1. The Synergy between IoT and AI Is a Strategic Imperative: Fully exploiting the potential of renewable energy systems, energy storage technologies, and demand response mechanisms in residential environments requires intelligent, data-driven control frameworks that can only be achieved through the integration of the monitoring capabilities of the Internet of Things with the decision-making intelligence of Artificial Intelligence [9, 15].
2. Reinforcement Learning Algorithms Have Become the Dominant Approach: Owing to their exceptional capability to learn optimal control policies in dynamic and uncertain environments, Deep Reinforcement Learning has emerged as one of the most effective methodologies for smart home energy management. Hybrid approaches, including fuzzy reinforcement learning and metaheuristic optimization techniques, have further enhanced the efficiency and robustness of these systems [21, 22].
3. A Significant Gap Exists Between Theory and Practice: Despite remarkable achievements in simulation environments, practical deployment continues to face substantial challenges, including communication latency, noisy sensor data, cybersecurity threats, and user interaction issues, all of which hinder the widespread adoption of these technologies [8, 26].
4. Lack of Integrated Management Frameworks: Most existing studies focus on single-resource optimization—primarily energy—while giving relatively limited attention to the complex interactions and synergies between water and energy subsystems within integrated, real-time management frameworks [7, 19].

5- CONCLUSION AND FUTURE PERSPECTIVES

This review has provided a comprehensive overview of the theoretical foundations, applications, and challenges associated with the synergistic integration of Artificial Intelligence and the Internet of Things for optimal water and energy management in smart homes. The

findings demonstrate that these technologies possess significant potential to facilitate a sustainable transformation of the residential sector by substantially reducing operational costs and environmental emissions while simultaneously enhancing user comfort and system interactivity.
Nevertheless, achieving this vision requires overcoming several critical challenges, which demand coordinated research and practical efforts in the following key areas:

1. Development of Integrated Water-Energy Management Frameworks: Future research should focus on comprehensive models that address the interactions and mutual constraints between these two critical resources rather than treating them as independent optimization problems [7]. The modeling of integrated systems such as ITHERST represents an important step in this direction [19].

2. Enhancing Security and Privacy through Advanced Architectures: Implementing Security-by-Design principles and adopting emerging technologies such as blockchain and federated learning to safeguard data privacy are essential for building public trust and promoting the widespread adoption of smart home technologies [26].

3. Development of Efficient and Robust Learning Methods: Advancing toward algorithms capable of maintaining reliable performance with limited training data and under realistic operating conditions—including communication delays and sensor noise—such as transfer learning and meta-learning, constitutes a major research priority [8].

4. Providing Transparent Scenario-Based Economic Analyses: Developing rigorous and practical economic models that account for various pricing mechanisms, subsidy policies, and infrastructure costs to produce realistic estimates of Return on Investment (ROI) can play a pivotal role in accelerating informed decision-making and investment in smart home technologies [27].

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