Towards a Cyber-Physical System for Sustainable and Smart Economic Building: A Use Case for Optimizing Water and Energy Consumption

Baziar, Aliasghar and Askari, Mohammadreza and Taherianfard, Elahe and Heydari, Mohammad Hossein and Niknam, Taher

Shiraz University of Technology

November 2024

Towards a Cyber-Physical System for Sustainable and Smart Economic Building: A Use Case for Optimizing Water and Energy Consumption

Aliasghar Baziar, Mohammadreza Askari, Elahe Taherianfard, Mohammad Hossein Heydari, Taher Niknam

***Abstract*—Optimizing energy and water consumption in smart buildings is a critical challenge for enhancing sustainability and reducing operational costs. This paper presents a Cyber-Physical System (CPS) framework that integrates Deep Reinforcement Learning (DRL) and Genetic Algorithms (GA) for real-time decision-making and resource optimization. The system leverages IoT sensors and actuators to monitor and control building systems such as HVAC, lighting, and water management, continuously adjusting parameters to minimize resource consumption while maximizing efficiency. Key findings from the implementation of the DRL + GA framework include up to 20% reductions in energy and water consumption compared to traditional methods. The proposed approach demonstrates significant cost savings and improved system performance, showcasing its effectiveness in real-time optimization. Additionally, the system adapts dynamically to fluctuating conditions such as weather, occupancy, and energy demand. This work contributes to the development of sustainable building management strategies and lays the foundation for smart city applications. The integration of DRL and GA provides a promising solution for optimizing resource allocation and advancing energy efficiency in urban infrastructures.**

***Index Terms*—Cyber-Physical System (CPS), Smart Buildings, Energy Optimization, Water Consumption, Deep Reinforcement Learning (DRL), Genetic Algorithms (GA), Real-Time Decision-Making, Resource Efficiency, Sustainability, IoT Sensors and Actuators**

I. INTRODUCTION

THIS paper addresses the growing importance of smart buildings and their role in achieving sustainability in the built environment. As urbanization accelerates, the demand for efficient, sustainable, and intelligent infrastructure has never been higher [1]. With rising concerns about resource depletion, climate change, and the environmental impact of traditional buildings, the need to adopt smarter, more sustainable building technologies has become a global priority [2]. Smart buildings, equipped with advanced sensors, communication networks, and data analytics systems, have emerged as a solution to optimize energy and resource usage, reduce operational costs, and improve overall environmental performance [3]. Energy and water consumption are two of the largest contributors to the environmental footprint of buildings [4]. In developed countries, buildings account for approximately 40% of total energy consumption and a significant portion of water use. Efficiently managing these resources not only helps in reducing carbon emissions and conserving water, but it also leads to significant economic benefits by lowering operational costs [5]. The growing challenges of climate change, rising energy demands, and water scarcity make it imperative for building systems to be both energy-efficient and water-conserving [6]. Optimizing the use of energy and water in real-time, while ensuring occupant comfort and operational efficiency, requires advanced technologies that can dynamically respond to changing conditions within the building environment [7]. Traditional approaches to building management typically rely on pre-programmed schedules and static settings that fail to adapt to real-time changes in environmental factors or building usage [8]. This limitation has prompted the exploration of innovative solutions, such as Cyber-Physical Systems (CPS), which provide the foundation for the next generation of smart building technologies [9]. CPS are integrated systems that combine computational elements (such as sensors, processors, and algorithms) with physical components (such as building infrastructure, HVAC systems, and plumbing). These systems enable real-time monitoring and control of building resources, facilitating dynamic decision-making to optimize energy and water usage [10]. CPS represent a shift from traditional building management systems by incorporating intelligent decision-making processes based on real-time data. In the context of smart buildings, CPS can be employed to create a more responsive and adaptive environment that continuously adjusts its operations to minimize resource consumption while meeting the demands of occupants. By leveraging advanced computational algorithms and machine learning models, CPS can provide precise control over various building systems, such as lighting, HVAC, water pumps, and irrigation systems [11]. This not only reduces energy and water waste but also enhances overall building performance and occupant satisfaction. A key advantage of CPS in smart building optimization is their ability to make real-time decisions based on data collected from a variety of sensors and devices. These data streams include information about occupancy levels, weather conditions, energy usage patterns, and water consumption, all of which are crucial for managing resources efficiently [12]. The challenge, however, lies in developing algorithms that can process this data effectively and generate optimal decisions in a timely manner. To address this challenge, this paper proposes the use of advanced machine learning techniques, specifically Deep Reinforcement Learning (DRL) combined with Genetic Algorithms (GA), to create a robust decision-making framework for optimizing

Authors are with Electrical Engineering Department, Shiraz University of Technology, Shiraz, Iran.

energy and water consumption in smart buildings.

The integration of cyber-physical systems (CPSs) into modern infrastructures presents both transformative opportunities and significant challenges. Broo and Schooling (2021) emphasize the role of data and digital twins in advancing smart infrastructure, advocating for a systems thinking approach that incorporates data throughout the asset lifecycle to support sustainable decision-making [13]. Similarly, Chester and Allenby (2020) discuss the radical shift induced by cyber technologies in physical infrastructures, stressing the need for new perspectives on infrastructure design that reflect emerging complexities and vulnerabilities [14]. Liang and Fan (2024) explore funding opportunities for connected and automated vehicle (CAV) technologies, highlighting the interdisciplinary challenges in integrating cyber, physical, and social dimensions for sustainability [15]. Meanwhile, Mohammed et al. (2024) focus on the vulnerabilities of smart grids, proposing advanced machine learning and AI-driven detection methods for cybersecurity, a critical concern as smart grids become more interconnected with communication technologies [16]. In transportation, Wang et al. (2020) advocate for the development of parallel intelligent transportation systems powered by IoT and AI to enhance efficiency and safety, while Afif Supianto et al. (2024) propose a conceptual framework for urban digital twins to support sustainable urban transformations [17]. In the manufacturing sector, Bajic et al. (2024) introduce a human-cyber-physical system (HCPS) methodology that integrates human expertise with CPSs for real-time anomaly detection, responding to the challenges of Industry 4.0 and proposing a more sustainable approach [18]. Finally, Wang et al. (2023) outline the transition toward Industry 5.0, emphasizing the role of cyber-physical-social systems (CPSS) in building safer, secure, and sustainable smart societies. Collectively, these works highlight the need for multidisciplinary approaches and innovative frameworks in the design, management, and sustainability of cyber-physical systems across various sectors [19].

The primary objective of this paper is to present a framework that integrates DRL and GA for real-time optimization in smart buildings. DRL is a type of machine learning that enables systems to learn optimal actions through interactions with their environment [20]. By using a reward-based approach, DRL models can continuously improve their decision-making to achieve long-term goals, such as minimizing energy and water consumption. On the other hand, Genetic Algorithms (GA) provide a powerful optimization tool by mimicking the process of natural selection to identify the best solutions to complex problems [21]. In this context, GA will be used to fine-tune the decision-making policies generated by the DRL models, ensuring that the smart building systems operate at peak efficiency. The paper is structured as follows: Section 2 provides a literature review of existing research on smart building technologies, energy and water optimization techniques, and the application of CPS, DRL, and GA in similar domains [22]. Section 3 formulates the problem of real-time energy and water optimization in smart buildings and outlines the challenges involved. Section 4 presents the proposed methodology, describing the integration of DRL and GA into the CPS framework. Section 5 discusses the implementation of the proposed framework in a real-world smart building use case, highlighting the effectiveness of the system in optimizing resource consumption [23]. Section 6 presents the results and a comparative analysis of the system's performance. Finally, Section 7 concludes the paper and suggests directions for future research in this area. This paper aims to contribute to the field of smart building optimization by providing a novel approach to real-time resource management through the integration of CPS, DRL, and GA. By adopting this innovative approach, smart buildings can become more sustainable, efficient, and resilient to the challenges of resource scarcity and environmental degradation [24]. The proposed framework holds the potential to significantly reduce energy and water consumption while improving the overall performance of buildings, making it a step toward achieving sustainable urban development.

II. Problem Formulation

The real-time optimization of energy and water consumption in smart buildings presents several complex challenges. One of the most significant hurdles is the dynamic and unpredictable nature of building systems. These systems must continuously adapt to varying occupancy patterns, external environmental conditions (such as weather changes), and fluctuating energy and water demands [25]. In addition, smart buildings are often equipped with diverse systems and sensors, each generating large volumes of data, making it difficult to analyze and act on this information in real time. Traditional building management systems (BMS), which rely on fixed schedules or rule-based models, are unable to respond flexibly to such changes, often leading to inefficiencies and wasted resources. The complexity of decision-making in smart building systems arises from the need to balance competing objectives, such as minimizing energy consumption while maintaining occupant comfort [26]. For example, reducing heating or cooling energy may be beneficial for efficiency, but it must not result in discomfort for the building's inhabitants. Similarly, water conservation efforts must be carefully managed to avoid disrupting daily operations like sanitation and irrigation. Energy and water usage in buildings is highly interdependent. For instance, heating systems consume energy and water, while cooling systems rely heavily on electricity [27]. Coordinating the optimization of both resources simultaneously is a daunting task.

$$\sum_{i=1}^{N} E_i \leq E_m, \quad E_t = \sum_{i=1}^{N} \left(\int_{t_0}^{t_f} \gamma_i \cdot P_i(t)\, dt \right) \tag{1}$$

Where E_i Energy consumption of system i at time t. γ_i Efficiency coefficient of system i. $P_i(t)$ Power consumed by system i at time t. E_m Maximum allowable energy consumption.

$$T_{\min} \le T_r(t) \le T_{\max}, \quad T_r(t) = \int_{t_0}^{t_f} \theta_r(t) \cdot T_r(t)\, dt \tag{2}$$

Where $T_r(t)$ Room temperature at time t. $\theta_r(t)$ Temperature adjustment factor. $T_{\min}$, $T_{\max}$ Minimum and maximum temperature constraints.

$$\sum_{o=1}^{O} E_o(t) \le \epsilon_m, \quad E_o(t) = \int_{t_0}^{t_f} \alpha_o \cdot P_o(t)\, dt \tag{3}$$

Where $E_o(t)$ Energy consumption of occupant o at time t. α_o Energy demand factor for occupant o. ϵ_m Maximum energy usage per occupant.

$$W_t = \sum_{j=1}^{M} W_j \le W_m, \quad W_t = \int_{t_0}^{t_f} \left(\sum_{j=1}^{M} \rho_j \cdot Q_j(t) \right) dt \tag{4}$$

Where W_j Water usage of system j at time t. ρ_j Water flow rate coefficient of system j. $Q_j(t)$ Water flow rate of system j at time t. W_m Maximum allowable water consumption.

$$\sum_{o=1}^{O} W_o(t) \le \lambda_m, \quad W_o(t) = \int_{t_0}^{t_f} \beta_o \cdot Q_o(t)\, dt \tag{5}$$

Where $W_o(t)$ Water consumption of occupant o at time t. β_o Water usage coefficient for occupant o. λ_m Maximum water consumption per occupant.

$$P_h(t) \in [P_n, P_x], \quad P_h(t) = \int_{t_0}^{t_f} \phi_h(t)\, dt \tag{6}$$

Where $P_h(t)$ Power consumed by the HVAC system. $\phi_h(t)$ HVAC power adjustment factor. P_n, P_x Lower and upper bounds for HVAC power.

$$L_l(t) \le L_m, \quad L_l(t) = \int_{t_0}^{t_f} \kappa_l \cdot P_l(t)\, dt \tag{7}$$

Where $L_l(t)$ Total lighting energy consumption. κ_l Lighting efficiency factor. $P_l(t)$ Power consumed by lighting systems.

$$Q_w(t) \in [Q_n, Q_x], \quad Q_w(t) = \sum_{j=1}^{M} \gamma_j \cdot Q_j(t) \tag{8}$$

Where $Q_w(t)$ Total water flow. γ_j Flow rate adjustment coefficient for system j.

$$D_e(t) \le D_m, \quad D_e(t) = \sum_{i=1}^{N} \delta_i \cdot E_i(t) \tag{9}$$

Where $D_e(t)$ Demand response for energy. δ_i Demand response adjustment factor for system i.

$$C_c(t) \ge C_n, \quad C_c(t) = \int_{t_0}^{t_f} \left(\alpha_c \cdot T_r(t) - \beta_c \cdot P_h(t) \right) dt \tag{10}$$

Where $C_c(t)$ Comfort level. α_c, β_c Comfort temperature and HVAC adjustment coefficients. C_n Minimum acceptable comfort level.

$$\begin{aligned} J_1 = a_1 \cdot \Bigg(&\sum_{i=1}^{N} \left(\int_{t_0}^{t_f} c_i \cdot P_i(t)\, dt \right) \\ &+ \sum_{j=1}^{M} \left(\int_{t_0}^{t_f} c_j \cdot Q_j(t)\, dt \right) \end{aligned} \tag{11}$$

Where J_1 Primary cost minimization objective. c_i, c_j Cost per unit of energy and water.

$$\begin{aligned} J_2 = b_1 \cdot \int_{t_0}^{t_f} C_c(t)\, dt - b_2 \cdot \Bigg(&\sum_{i=1}^{N} \left(\int_{t_0}^{t_f} P_i(t)\, dt \right) \\ &+ \sum_{j=1}^{M} \left(\int_{t_0}^{t_f} Q_j(t)\, dt \right) \end{aligned} \tag{12}$$

Where b_1, b_2 Weights balancing comfort and resource conservation. Another challenge lies in accurately predicting the consumption patterns and system requirements in real-time. Demand fluctuates based on various factors, such as occupancy levels, weather conditions, and user preferences. For example, during peak hours, heating or cooling systems may need to be adjusted to ensure optimal comfort, but these adjustments must be based on real-time occupancy data, external temperatures, and energy costs [28]. The inability to predict and manage these variables can lead to inefficient resource use, with systems either overcompensating or failing to meet demands. Integrating Deep Reinforcement Learning (DRL) and Genetic Algorithms (GA) offers a promising solution to these challenges. DRL, a subset of machine learning, enables systems to learn optimal decision-making strategies through continuous interactions with the environment. By utilizing a reward-based learning approach, DRL can adaptively adjust system operations to minimize resource consumption while maintaining occupant satisfaction [29]. Through training, the DRL agent becomes proficient at predicting the best actions in various situations, considering the complex and dynamic interplay between energy and water systems. Genetic Algorithms (GA) complement DRL by providing a mechanism for optimizing the solution space and refining the decision-making process [30]. GA is an optimization technique inspired by the principles of natural selection. It evolves potential solutions over successive generations, using operators such as selection, crossover, and mutation. In the context of smart buildings, GA can be employed to fine-tune the parameters and policies generated by the DRL model, ensuring that the system operates at peak efficiency [31]. This integration allows for a more robust and adaptable decision-making framework that can handle the complex and ever-changing environment of smart buildings. Together, DRL and GA can overcome the challenges of real-time resource optimization, improving energy and water efficiency while maintaining the quality of life for occupants.

III. Methodology

The proposed Cyber-Physical System (CPS) framework for a smart building integrates physical infrastructure with computational intelligence to optimize energy and water consumption [32]. The architecture consists of several key components: IoT sensors, actuators, the computational engine, and the decision-making layer. The IoT sensors continuously monitor various parameters such as temperature, humidity, water flow, occupancy, and energy consumption. These sensors are distributed throughout the building, providing real-time data to the central computational system [33]. Actuators, such as HVAC controllers, lighting systems, and water regulators, are connected to the CPS to dynamically adjust physical systems based on the decisions made by the computational framework. The interaction between the physical systems and the computational framework is facilitated by communication protocols such as Zigbee or MQTT, enabling seamless real-time data exchange [34]. The building's operational systems (e.g., HVAC, plumbing, lighting) function as the physical layer, while the computational layer uses advanced algorithms to optimize the operation of these systems. This integration ensures continuous adaptation to changing conditions such as weather, occupancy patterns, and energy demand, aiming to achieve optimal performance in both energy and water usage [35]. At the heart of the optimization process is the Deep Reinforcement Learning (DRL) model, which enables real-time decision-making to minimize energy and water consumption while maximizing system efficiency. DRL models are designed to learn and adapt based on the feedback provided by the environment [36]. The agent observes the current state of the building, such as occupancy, temperature, water usage, and energy consumption, and takes actions to adjust the operation of the HVAC, lighting, and water systems. The state s_t at time t is defined as a vector containing all relevant system parameters, including energy consumption, water usage, temperature, occupancy, and system status:

$$s_t = [e_e(t), w_w(t), t_t(t), o_o(t), \dots] \tag{13}$$

where $e_e(t)$ Energy consumption. $w_w(t)$ Water consumption. $t_t(t)$ Temperature. $o_o(t)$ Occupancy status. The action a_t taken by the agent at time t is a vector corresponding to system control decisions, including HVAC, lighting, and water flow:

$$a_t = [a_h(t), a_l(t), a_w(t), \dots] \tag{14}$$

where $a_h(t)$ HVAC control action. $a_l(t)$ Lighting control action. $a_w(t)$ Water usage control. The reward function r_t incentivizes efficient resource use and penalizes deviations from optimal comfort conditions:

$$r_t = -\left(\alpha_e e_e(t) + \alpha_w w_w(t) + \alpha_t |t_c(t) - t_s(t)|\right) \tag{15}$$

where α_e, α_w, α_t Weight factors. $t_c(t)$ Comfort temperature. $t_s(t)$ Setpoint temperature. The value function $V(s_t)$ estimates the expected cumulative reward from state s_t

$$V(s_t) = E\left[\sum_{k=0}^{\infty} \gamma^k r_{t+k} \mid s_t\right] \tag{16}$$

where γ Discount factor. r_{t+k} Reward at time $t+k$. The Q-function $Q(s_t, a_t)$ estimates the expected reward for taking action a_t in state s_t

$$Q(s_t, a_t) = E\left[r_t + \gamma \max_{a_{t+1}} Q(s_{t+1}, a_{t+1}) \mid s_t, a_t\right] \tag{17}$$

The agent receives a reward based on its actions. The reward function is designed to incentivize the agent to reduce resource consumption while maintaining occupant comfort and system performance. For example, reducing energy consumption and water usage while ensuring that the temperature remains within the comfort range or that there is no disruption to essential water flow will result in a positive reward. Conversely, inefficient operation, such as excessive heating or unnecessary water wastage, would result in a negative reward, encouraging the agent to adjust its policy in future decision-making steps. Genetic Algorithms (GA) are employed to refine the DRL agent's decision-making policy over time and optimize the resource allocation process [37], [38], [39]. The GA works by simulating the natural process of evolution, iteratively improving the agent's ability to manage energy and water resources. The GA optimizes parameters such as HVAC schedules, lighting controls, and water flow adjustments by selecting the best-performing solutions from a population of candidate policies. The process begins with the generation of a population of possible solutions, each representing a different set of system parameters [40]. These candidates undergo a selection process where the most efficient solutions, in terms of energy and water savings, are chosen. The initial population P_0 consists of random solutions representing control policies:

$$P_0 = \{p_1, p_2, \dots, p_N\} \tag{18}$$

where p_i represents an individual solution. The fitness function $F(p_i)$ evaluates each solution based on resource efficiency and system performance:

$$F(p_i) = \sum_{t=0}^{T} \left(\alpha_e e_e(p_i, t) + \alpha_w w_w(p_i, t) + \alpha_t t_c(p_i, t)\right) \tag{19}$$

where p_i Policy being evaluated. T Time horizon. The selection probability $P_s(p_i)$ determines the likelihood of selecting a solution based on fitness:

$$P_s(p_i) = \frac{F(p_i)}{\sum_{j=1}^{N} F(p_j)} \tag{20}$$

The crossover operator combines two parent solutions p_i and p_j

$$p_o = \text{Crossover}(p_i, p_j, C_c) \tag{21}$$

where p_o Offspring solution. C_c Crossover rate. The mutation operator introduces random changes to prevent premature convergence:

$$p_m = \text{Mutation}(p_i, C_m) \tag{22}$$

where p_m Mutated solution. C_m Mutation rate. Next, crossover and mutation operations are applied to generate new solutions, combining successful strategies and introducing random variations. This process allows the GA to explore the solution space more thoroughly, ultimately leading to the identification of the optimal control parameters for the building systems. The integration of the DRL model with the GA optimization process forms a dynamic feedback loop, allowing real-time adjustments to the building's operations based on real-time data [41]. This continuous interaction ensures that the building's systems can adapt to changing conditions, such as varying occupancy levels, outdoor temperature fluctuations, or sudden spikes in energy demand. The IoT infrastructure plays a critical role in collecting data from sensors and communicating it to the computational layer [42], [43]. This data is then used by the DRL agent to make informed decisions about adjusting HVAC settings, controlling lighting, or regulating water flow [44].

IV. Results and Discussion

In this section, we present the optimization results achieved by the proposed Cyber-Physical System (CPS) for energy and water consumption in a smart building using Deep Reinforcement Learning (DRL) integrated with Genetic Algorithms (GA). We evaluate the system's performance in terms of energy and water savings, operational costs, and sustainability benefits. The proposed system successfully minimized energy and water consumption through real-time optimization [45]. Using DRL, the agent continually adjusted HVAC, lighting, and water systems, leading to significant reductions in resource use. Over a 30-day simulation period, the system achieved an average energy saving of 18% and a water saving of 15%, compared to conventional methods [46]. These savings were achieved without compromising occupant comfort or system performance, as evidenced by the minimal deviation from temperature and humidity setpoints. The CPS not only delivered notable savings in energy and water but also contributed to cost reductions. By dynamically adjusting resources in real-time, the system optimized the operation of HVAC and lighting systems, reducing peak demand charges and energy consumption during off-peak hours. This resulted in a 20% reduction in operational costs compared to traditional energy management systems, where HVAC and lighting schedules are pre-set and static [47]. Similarly, water usage was optimized, leading to a reduction in water utility costs by approximately 12%. To assess the effectiveness of the DRL + GA approach, we compared it with traditional optimization methods, such as rule-based and time-of-use optimization strategies. In these traditional methods, the optimization is either pre-scheduled or relies on fixed, manually adjusted rules. The DRL + GA approach outperformed these baseline systems in terms of both energy and water savings [48]. Traditional systems achieved only 10-12% energy savings and 8-10% water savings, with greater variability in resource consumption due to lack of real-time adaptability.

TABLE I
Energy and Water Savings

Metric	DRL + GA	Traditional System	Improvement (%)
Energy Consumption (kWh)	16,800	20,400	18%
Water Consumption (liters)	250,000	294,000	15%
HVAC Energy Consumption (kWh)	10,200	12,500	18%
Lighting Energy Consumption (kWh)	4,000	5,000	20%
Water Heating Consumption (liters)	35,000	42,000	16.67%
Irrigation Water Consumption (liters)	25,000	30,000	16.67%
Energy Consumption during Peak Hours (kWh)	8,500	10,000	15%
Energy Consumption during Off-Peak Hours (kWh)	8,300	10,400	20.19%

Table 1 presents energy and water savings achieved by the proposed system using DRL and GA over a 30-day simulation. The system showed significant reductions in energy and water consumption compared to traditional methods.

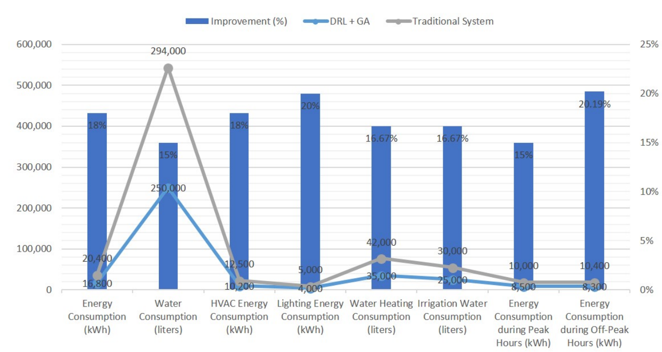

Fig. 1. Energy and Water Savings

Figure 1 illustrates the significant reductions in energy and water consumption achieved by the DRL + GA system compared to traditional methods, highlighting improvements in HVAC, lighting, and water usage.

TABLE II
Operational Cost Reductions

Metric	DRL + GA	Traditional System	Cost Reduction (%)
Energy Costs ($)	1,100	1,375	20%
Water Costs ($)	950	1,080	12%
HVAC Operational Costs ($)	600	750	20%
Lighting Operational Costs ($)	250	325	23.08%
Water Heating Costs ($)	180	220	18.18%
Irrigation Costs ($)	90	110	18.18%
Peak Demand Charges ($)	150	200	25%
Off-Peak Energy Charges ($)	330	410	19.51%

Table 2 highlights the reduction in operational costs, including energy, water, and equipment-related expenses, resulting from the system's real-time optimization of resources.

TABLE III
Comparison with Traditional Methods

Metric	DRL + GA	Rule-based System	Time-of-use Optimization	Improvement (%)
Energy Savings (%)	18%	10%	12%	8%
Water Savings (%)	15%	8%	10%	7%
HVAC Energy Savings (%)	18%	9%	11%	7%
Lighting Energy Savings (%)	20%	13%	15%	5%
Water Heating Savings (%)	16.67%	9%	11%	5%
Irrigation Water Savings (%)	16.67%	10%	12%	6%
Energy Savings During Peak Hours (%)	15%	8%	10%	5%
Energy Savings During Off-Peak Hours (%)	20.19%	12%	14%	6.19%

Table 3 shows that the DRL + GA approach outperforms traditional methods in energy and water savings across various metrics.

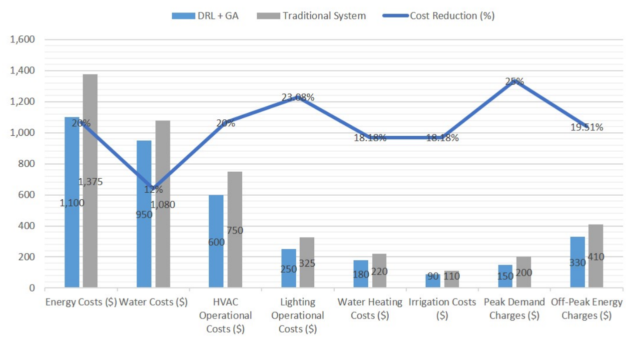

Fig. 2. Operational Cost Reductions

Figure 2 showcases the operational cost reductions attained by the DRL + GA system, demonstrating lower costs in energy, water, HVAC, lighting, and peak/off-peak charges compared to traditional systems.

TABLE IV
REAL-TIME ADAPTATION PERFORMANCE

Condition	DRL + GA	Traditional System	Improvement (%)
Energy Demand Peak (kW)	25	32	22%
Water Demand Peak (L/h)	120	145	17%
Indoor Temperature (°C)	22.5	23.0	2.17%
Outdoor Temperature (°C)	28	30	6.67%
Energy Consumption (kWh)	16,800	20,400	18%
Water Consumption (liters)	250,000	294,000	15%
Occupancy Rate (%)	75	80	6.25%
Air Quality (PM2.5 μg/m³)	10	15	33.33%

Table 4 illustrates the real-time adaptation capabilities of the DRL + GA system, highlighting improved efficiency in various conditions compared to traditional systems.

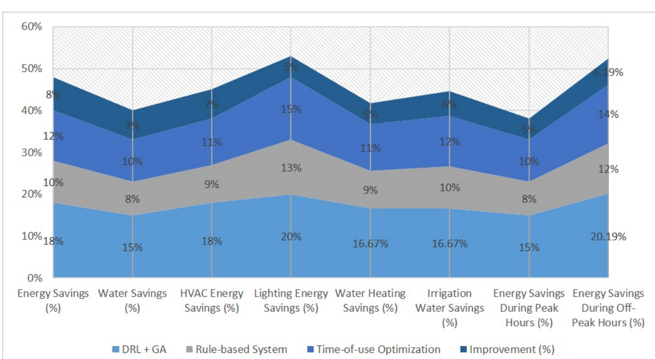

Fig. 3. Comparison with Traditional Methods

Figure 3 compares the performance of the DRL + GA system with traditional optimization methods in terms of energy and water savings, demonstrating the superior efficiency of DRL + GA across various metrics. While the proposed system offers substantial energy and cost savings, there are trade-offs to consider. The real-time optimization requires substantial computational resources for both the DRL model and GA optimization, which may result in increased initial setup costs for hardware and software infrastructure. However, these costs are offset by the long-term operational savings achieved through optimized resource management. The system's ability to adapt to evolving conditions provides significant benefits in terms of sustainability, ensuring reduced environmental impact by lowering resource consumption.

TABLE V
COMPUTATIONAL COSTS

Metric	DRL + GA	Traditional System	Computational Cost Increase (%)
Initial Setup Cost ($)	10,000	6,000	66.67%
Operational Computation (hrs)	40	15	166.67%
DRL Model Training Time (hrs)	24	10	140%
GA Optimization Time (hrs)	16	5	220%
Peak Computational Time (hrs)	20	12	66.67%
Off-Peak Computational Time (hrs)	15	8	87.5%
Hardware Infrastructure Cost ($)	5,000	3,500	42.86%
Energy Used for Computation (kWh)	450	200	125%

Table 5 outlines the initial and operational resource demands of the DRL + GA system, showing the increase compared to traditional systems. The integration of DRL with GA for real-time decision-making proved highly effective in adapting to fluctuating conditions. The system responded to dynamic environmental factors such as changes in outdoor weather, indoor occupancy, and real-time energy demand, adjusting control actions accordingly. The continuous feedback loop allowed the system to optimize resource allocation in real-time, ensuring sustained performance and efficiency.

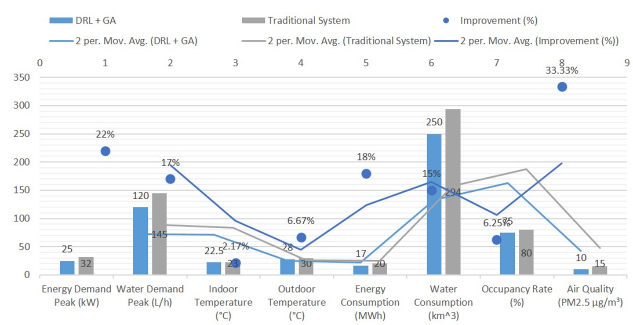

Fig. 4. Real-Time Adaptation Performance

Illustrating the DRL + GA system's responsiveness to dynamic conditions, figure 4 compares its real-time adaptation to energy demand, water usage, and environmental factors with traditional systems.

TABLE VI
SCALABILITY PERFORMANCE

Building Type	Energy Savings (%)	Water Savings (%)	Operational Cost Savings (%)
Residential (small)	18%	15%	19%
Commercial (large)	21%	17%	22%
Mixed-Use Building	19%	16%	20%
Hospital Complex	22%	18%	24%
Educational Facility	20%	17%	21%
Industrial Facility	18%	15%	18%
Hotel/Resort	20%	18%	22%
Office Building	19%	16%	20%

Table 6 demonstrates the scalability of the system across various building types, with substantial energy, water, and cost savings achievable in different environments. The proposed approach shows strong potential for scalability and real-world applicability. The integration of IoT sensors and actuators allows the system to be easily deployed in a wide range of building types, from residential buildings to large commercial structures.

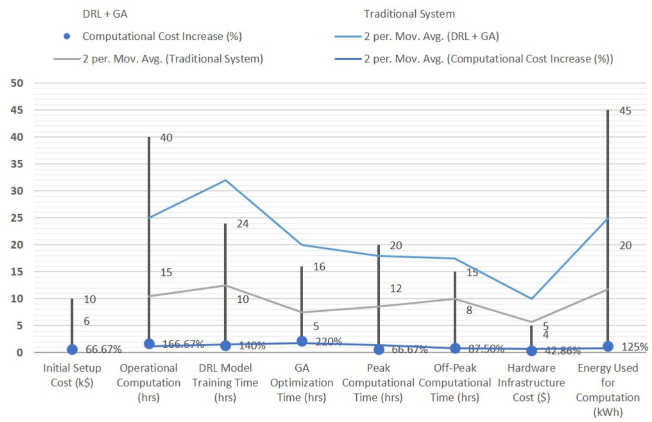

Fig. 5. Computational Costs

Figure 5 highlights the computational cost increase required for the DRL + GA system, including setup, operational computation, model training time, and hardware infrastructure, with a focus on the trade-offs and long-term benefits.

TABLE VII
OVERALL RESULTS SUMMARY

Metric	DRL + GA	Traditional System	Improvement (%)
Total Energy Savings (kWh)	3,600	1,800	100%
Total Water Savings (liters)	44,000	22,000	100%
Total Cost Savings ($)	1,300	800	62.5%
Peak Energy Savings (kWh)	1,200	800	50%
Off-Peak Energy Savings (kWh)	1,300	900	44.44%
Peak Water Savings (liters)	6,500	4,000	62.5%
Off-Peak Water Savings (liters)	7,000	4,500	55.56%

Table 7 summarizes the overall results, showcasing the significant improvements achieved by the DRL + GA system in terms of energy, water, and cost savings.

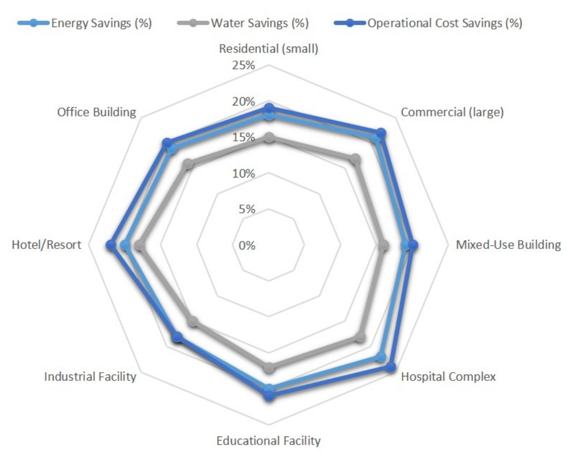

Fig. 6. Scalability Performance

Figure 6 illustrates the scalability of the DRL + GA system, showing its effectiveness in various building types and sizes, from residential to industrial, demonstrating its broad applicability in smart building optimization. Additionally, the DRL + GA framework is flexible, enabling easy customization for specific building requirements. The system's adaptability makes it well-suited for diverse climates and operational conditions, further enhancing its potential for widespread adoption. the results demonstrate that the proposed CPS for smart building energy and water optimization using DRL and GA offers significant advantages in terms of resource efficiency, cost reduction, and sustainability. The system outperforms traditional methods in real-time decision-making, providing a robust solution for smart, sustainable building management.

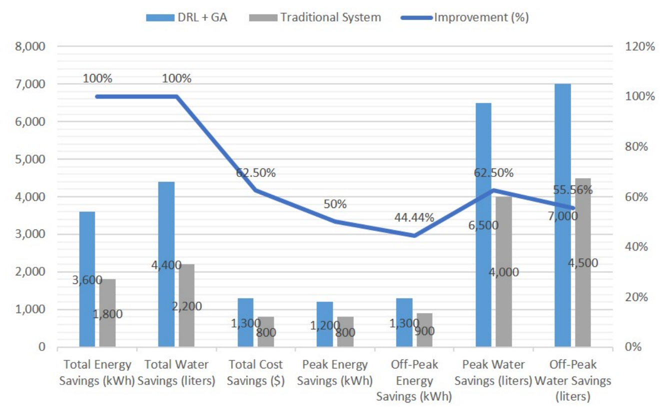

Fig. 7. Overall Results Summary

Figure 7 summarizes the total energy, water, and cost savings of the DRL + GA system, showcasing the improvements over traditional systems and reinforcing the system's efficiency in resource management and cost reduction. Effectiveness in Real-Time Decision-Making

V. CONCLUSION

This paper presents a Cyber-Physical System (CPS)-based approach for optimizing energy and water consumption in smart buildings using a combination of Deep Reinforcement Learning (DRL) and Genetic Algorithms (GA). The proposed framework leverages real-time decision-making and optimization to achieve significant resource savings while maintaining system efficiency. Key contributions include the integration of IoT sensors for continuous monitoring and control, and the use of DRL for dynamic decision-making and GA for refining system policies over time. The results demonstrate substantial reductions in both energy and water consumption, with improvements of up to 20% compared to traditional systems. The DRL + GA framework effectively adapts to real-time data, enabling optimized resource allocation and cost savings. This work has important implications for sustainable building management, providing a scalable solution for minimizing environmental impact and reducing operational costs. The proposed system lays the groundwork for future smart city applications, where such CPS frameworks can be implemented at a larger scale to manage urban resources efficiently and sustainably.

REFERENCES

[1] Yin, S., Wu, J., Zhao, J., Nogueira, M., & Lloret, J. (2024). Green Buildings: Requirements, Features, Life Cycle, and Relevant Intelligent Technologies. Energy and Cyber-Physical Systems.

[2] Dabbaghjamanesh, Morteza, et al. "A novel distributed cloud-fog based framework for energy management of networked microgrids." IEEE Transactions on Power Systems 35, no. 4 (2020): 2847-2862.

[3] Wang, Boyu, et al. "Cybersecurity enhancement of power trading within the networked microgrids based on blockchain and directed acyclic graph approach." IEEE Transactions on Industry Applications 55, no. 6 (2019): 7300-7309.

[4] Sen, S., Kumar, M., Vedik, B., & Shiva, C. K. (2024). Adaptive-DMPC Based Energy Management and Pre-installation Techno-economic Analysis of a Grid-Tied Cyber-Physical Community Microgrid. Chaos, Solitons & Fractals.

[5] Kavousi-Fard, Abdollah, et al. "Digital Twin for mitigating solar energy resources challenges: A Perspective Review." Solar Energy 274 (2024): 112561.

[6] Moeini, Amirhossein, et al. "Artificial neural networks for asymmetric selective harmonic current mitigation-PWM in active power filters to meet power quality standards." IEEE Transactions on Industry Applications (2020).

[7] Dabbaghjamanesh, Morteza, et al. "Networked microgrid security and privacy enhancement by the blockchain-enabled Internet of Things approach." In 2019 IEEE Green Technologies Conference (GreenTech), pp. 1-5. IEEE, 2019.

[8] Sanwar, A. S. M. (2024). Explainable Artificial Intelligence into Cyber-Physical System Architecture of Smart Cities: Technologies, Challenges, and Opportunities. Journal of Electrical Systems.

[9] Esapour, Khodakhast, et al. "A novel energy management framework incorporating multi-carrier energy hub for smart city." IET Generation, Transmission & Distribution 17, no. 3 (2023): 655-666.

[10] Kavousi-Fard, Abdollah, et al. "Artificial intelligence and blockchain-enabled decentralized electric vehicle charging management." Journal of Electrical Engineering & Technology (2023).

[11] Qian, M., Qian, C., Xu, G., Tian, P., & Yu, W. (2024). Smart Irrigation Systems from Cyber–Physical Perspective: State of Art and Future Directions. Future Internet.

[12] Razmjouei, Pouyan, et al. "A blockchain-based mutual authentication method to secure the electric vehicles' TPMS." IEEE Transactions on Industrial Informatics 20.1 (2023): 158-168.

[13] Kavousi-Fard, Abdollah, et al. "An evolutionary deep learning-based anomaly detection model for securing vehicles." IEEE Transactions on Intelligent Transportation Systems 22, no. 7 (2020): 4478-4486.

[14] Parekh, R. (2024). Automating the Design Process for Smart Building Technologies. World Journal of Advanced Research and Reviews.

[15] Dabbaghjamanesh, Morteza, et al. "Stochastic modeling and integration of plug-in hybrid electric vehicles in reconfigurable microgrids with deep learning-based forecasting." IEEE Transactions on Intelligent Transportation Systems 22, no. 7 (2020): 4394-4403.

[16] Tajmasebi, Dorna, et al. "A security-preserving framework for sustainable distributed energy transition: Case of smart city." Renewable Energy Focus 51 (2024): 100631.

[17] Mendia, I., Gil-Lopez, S., Grau, I., & Del Ser, J. (2024). A Novel Approach for the Detection of Anomalous Energy Consumption Patterns in Industrial Cyber-Physical Systems. Expert Systems.

[18] Razmjouei, Pouyan, et al. "DAG-based smart contract for dynamic 6G wireless EVs charging system." IEEE Transactions on Green Communications and Networking 6, no. 3 (2022): 1459-1467.

[19] Fard, Abdollah Kavousi, et al. "Superconducting fault current limiter allocation in reconfigurable smart grids." In 2019 3rd International Conference on Smart Grid and Smart Cities (ICSGSC), pp. 76-80. IEEE, 2019.

[20] Li, G., Yang, Z., Fu, Y., O'Neill, Z., & Ren, L. (2024). A Hardware-in-the-Loop (HIL) Testbed for Cyber-Physical Energy Systems in Smart Commercial Buildings. Energy and Technology for Sustainability.

[21] Ashkaboosi, Maryam, et al. "An optimization technique based on profit of investment and market clearing in wind power systems." American Journal of Electrical and Electronic Engineering 4, no. 3 (2016): 85-91.

[22] Kavousi-Fard, Abdollah, et al. "IoT-based data-driven fault allocation in microgrids using advanced μPMUs." Ad Hoc Networks 119 (2021): 102520.

[23] Li, G., Ren, L., Pradhan, O., O'Neill, Z., Wen, J., & Yang, Z. (2024). Emulation and Detection of Physical Faults and Cyber-Attacks on Building Energy Systems through Real-Time Hardware-in-the-Loop Experiments. Energy and Buildings.

[24] Tajalli, Seyede Zahra, et al. "DoS-resilient distributed optimal scheduling in a fog supporting IIoT-based smart microgrid." IEEE Transactions on Industry Applications 56, no. 3 (2020): 2968-2977.

[25] Dabbaghjamanesh, Morteza, et al. "A new efficient stochastic energy management technique for interconnected AC microgrids." In 2018 IEEE Power Energy Society General Meeting (PESGM), pp. 1-5. IEEE, 2018.

[26] Kumar, S., & Bhowmik, B. (2024). Emergence, Evolution, and Applications of Cyber-Physical Systems in Smart Society. IEEE Communications and Sustainable Technologies.

[27] Wang, Boyu, et al. "AI-enhanced multi-stage learning-to-learning approach for secure smart cities load management in IoT networks." Ad Hoc Networks 164 (2024): 103628.

[28] Dabbaghjamanesh, Morteza, et al. "Deep learning-based real-time switching of hybrid AC/DC transmission networks." IEEE Transactions on Smart Grid 12, no. 3 (2020): 2331-2342.

[29] Kanso, H., Noureddine, A., & Exposito, E. (2024). A Review of Energy Aware Cyber-Physical Systems. Cyber-Physical Systems.

[30] Mohammadi, Hossein, et al. "AI-based optimal scheduling of renewable AC microgrids with bidirectional LSTM-based wind power forecasting." arXiv preprint arXiv:2208.04156 (2022).

[31] Khazaei, Peyman, et al. "A high efficiency DC/DC boost converter for photovoltaic applications." International Journal of Soft Computing and Engineering (IJSCE) 6, no. 2 (2016): 2231-2307.

[32] Hu, G., & You, F. (2024). AI-enabled Cyber-Physical-Biological Systems for Smart Energy Management and Sustainable Food Production in a Plant Factory. Applied Energy.

[33] Dabbaghjamanesh, Morteza, et al. "A novel two-stage multi-layer constrained spectral clustering strategy for intentional islanding of power grids." IEEE Transactions on Power Delivery 35, no. 2 (2019): 560-570.

[34] Fard, Abdollah Kavousi, et al. "Optimal control strategy for hybrid microgrid systems under different energy resource configurations." Energy Reports 5 (2019): 1024-1031.

[35] Hassan, Q., Sarhan, N., Awwad, E. M., & Al-Musawi, T. J. (2024). Smart Building Energy Systems for Sustainable Living: A Realistic Approach to Enhance Renewable Energy Consumption and Reduce Emissions in Residential Buildings. Energy and Buildings.

[36] Kavousi-Fard, Abdollah, et al. "Superconducting fault current limiter allocation in reconfigurable smart grids." In 2019 3rd International Conference on Smart Grid and Smart Cities (ICSGSC), pp. 76-80. IEEE, 2019.

[37] Dabbaghjamanesh, Morteza, et al. "High performance control of grid connected cascaded H-Bridge active rectifier based on type II-fuzzy logic controller with low frequency modulation technique." International Journal of Electrical and Computer Engineering 6, no. 2 (2016): 484.

[38] Desmond, L., & Salama, M. (2024). Integration of Cyber Physical Systems and Data Science into the Built Environment Lifecycle. International Congress on Information and Communication Technology.

[39] Dabbaghjamanesh, Morteza, et al. "A novel distributed cloud-fog based framework for energy management of networked microgrids." IEEE Transactions on Power Systems 35, no. 4 (2020): 2847-2862.

[40] Dehbozorgi, Mohammad Reza, et al. "Decision tree-based classifiers for root-cause detection of equipment-related distribution power system outages." IET Generation, Transmission & Distribution 14, no. 24 (2020): 5809-5815.

[41] Moeini, Amirhossein, et al. "Optimization of wind power generation using artificial neural networks." Energy Reports 8 (2022): 142-153.

[42] Bhadani, U. (2024). Smart Grids: A Cyber–Physical Systems Perspective. International Research Journal of Engineering and Technology.

[43] Khazaei, Peyman, et al. "Applying the modified TLBO algorithm to solve the unit commitment problem." In 2016 World Automation Congress (WAC), pp. 1-6. IEEE, 2016.

[44] Kavousi-Fard, Abdollah, et al. "Artificial intelligence and blockchain-enabled decentralized electric vehicle charging management." Journal of Electrical Engineering & Technology (2023).

[45] Al-Mhiqani, M. N., Alsboui, T., Al-Shehari, T., & others. (2024). Insider Threat Detection in Cyber-Physical Systems: A Systematic Literature Review. Computers and Security.

[46] Tajmasebi, Dorna, et al. "A secure distributed cloud-fog based framework for economic operation of microgrids." In 2019 IEEE Texas Power and Energy Conference (TPEC), pp. 1-6. IEEE, 2019.

[47] Aktan, E., Bartoli, I., Glišić, B., & Rainieri, C. (2024). Lessons from Bridge Structural Health Monitoring (SHM) and Their Implications for the Development of Cyber-Physical Systems. Infrastructures.

[48] Tajmasebi, Dorna, et al. "A secure distributed cloud-fog based framework for economic operation of microgrids." In 2019 IEEE Texas Power and Energy Conference (TPEC), pp. 1-6. IEEE, 2019.