ISSN: 2458-8989

Natural and Engineering Sciences

NESciences, 2025, 10 (3): 807-818 doi: 10.28978/nesciences.1811161

Innovative Computational Models Integrating Artificial Intelligence and Genetic Algorithms for Sustainable Development in Smart IoT-Based Environment

Raya Karlibaeva [1*], Ali Bostani [2], Nurali Mavlonov [3], Robiya Niyozova [4], Zokir Mamadiyarov [5], Qodirov Oybek [6], Dr. Sumit Kushwaha [7]

[1*] Department of Finance and Tourism, Termez University of Economics and Service, Termez, Uzbekistan & Department of Finance, Tashkent State University of Economics, Tashkent, Uzbekistan. E-mail: raya.karlibaeva@tues.uz

[2] Associate Professor, College of Engineering and Applied Sciences, American University of Kuwait, Salmiya, Kuwait. E-mail: abostani@auk.edu.kw

[3] Head of the Department of Economics and Computer Engineering, International School of Finance Technology and Science, Tashkent, Uzbekistan. E-mail: nuralimavlonov111@gmail.com

[4] Senior Lecturer, Finance Department, Kimyo International University in Tashkent, Republic of Uzbekistan. E-mail: r.niyozova@kiut.uz

[5] Department of Finance, Alfraganus University, Tashkent, Uzbekistan; Department of Economics, Mamun University, Khiva, Uzbekistan. E-mail: z.mamadiyarov@afu.uz

[6] Department of Gistology, Sitology Va Embryology, Bukhara State Medical Institute named after Abu Ali ibn Sino, Bukhara, Republic of Uzbekistan. E-mail: oybek_qodirov@bsmi.uz

[7] Associate Professor, Department of Centre for Research and AI Development Learning Ecosystem (CRADLE) Cell, Chandigarh University Uttar Pradesh, Unnao, Uttar Pradesh, India. E-mail: sumit.kushwaha1@gmail.com

Abstract

Smart environments can be created with the help of the Internet of Things (IoT) technologies that have spread at such a pace that allows intelligent monitoring and management of vital resources. Nevertheless, an attainment of sustainable development in such settings is of great concern because of the dynamic resource needs, heterogeneity of systems and the constraints of the management strategies which are either statical or rule based. To combat such requirements, the paper will set forth a novel computational paradigm, integrating Artificial Intelligence and Genetic Algorithms, which were called a GA-Optimised Deep Neural Network (GA-DNN), to act as a sustainable resource management tool in a smart IoT-based

*Corresponding Author: Raya Karlibaeva, E-mail: raya.karlibaeva@tues.uz

setting (Zhang & Tao, 2020). The proposed solution incorporates a deep neural network which is used to model complex nonlinear relationships of the data provided by IoT sensors and other system control variables, the genetic algorithm is used to optimise the network parameters and hyper parameters to improve prediction efficiency and decision efficiency. The framework will be used to help optimise toward a multi-objective where the use of energy, resource utilisation efficiency, system latency, and sustainability influence can be taken into account. To test the effectiveness of the proposed GA-DNN model, a simulated multi-zone smart environment based on the simulated conditions of the real-world IoT deployment is used. The results of the experiment confirm that the suggested solution provides considerable increases in resource efficiency and sustainability indicators over current deep learning or rule-based methods of IoT management, and low compute latency that can be used in real-time work. The results point to the possibility of hybrid AI-based computational models as an efficient and scalable solution to the next generation of sustainable smart IoT environments.

Keywords:

Deep neural network, ga-optimized DNN, intelligent resource Management, Artificial Intelligence, Multi-Objective Optimization, Smart Environment Sustainability.

Article history:

Received: 19/07/2025, Revised: 06/09/2025, Accepted: 08/10/2025, Available online: 12/12/2025

Introduction

Internet of Things (IoT) technologies have rapidly advanced, which has made it possible to create smart environments that can continuously sense, make decisions based on the data, and autonomously control both urban, industrial, residential, and other spheres. These intelligent IoT environments can be significant in dealing with the global sustainability issues such as ensuring efficient use of energy, managing resources optimally, and reducing the effects on the environment. Recent literature speaks of the growing acceptance of artificial intelligence (AI) and data-oriented technologies in smart cities and smart environments to aid the sustainable development agenda (Andrews et al., 2022; Bibri et al., 2023; Brinda, 2025). Interference between AI, IoT and big data analytics has been cited as a pivotal source of enabling environmentally friendly smart ecosystems, and with better situational awareness and adaptive system behaviour (Bibri et al., 2023; Seng et al., 2022; Ali & Ashour, 2025).

Irrespective of these innovations, the majority of current IoT management systems are based on fixed algorithms of optimization or rules-based control, or predefined limits that do not have the ability to adapt to the changing environment or unequal demand on resources. These traditional strategies can hardly address nonlinear behaviour of system, variable workloads, multi-objective sustainability demands found regularly in real-world smart environments. Previous studies in the context of urban and smart planning have highlighted that traditional types of planning and optimization techniques are not scalable and adaptable in the face of data-intensive and sophisticated IoT infrastructures (Koumetio Tekouabou et al., 2023; Sanchez et al., 2023; Punam, 2025; Son et al., 2023). Consequently, the demand for adaptive and smart mechanisms of optimization that can learn and adapt to the dynamics of the systems has increased.

The techniques of artificial intelligence, especially the deep-learning models, have demonstrated high abilities in non-linear relationships modelling, and actionable insights extraction on a large scale IoT data stream (Marasinghe et al., 2024; Ali & Ashour, 2025; Sadulla, 2025). Nevertheless, deep neural networks (DNNs) require a lot of tuning in terms of network architecture, hyper parameters, and training settings, which are commonly evaluated through a heuristic or manual process. Genetic Algorithms (GAs) are based on the principles of evolution and provide an effective search of extensive search space and optimization of neural network parameters in a data-driven way. According to the recent AI-driven smart and sustainable system research, hybrid AI-driven systems are able to produce a massive improvement in the the system adaptability and decision effectiveness in comparison with monolithic learning models (Puri et al., 2019; Samadi, 2022; Punam, 2025). However, joint GA-optimised deep learning models of sustainable smart IoT environments are still not investigated actively (Senguttuvan & Karthikeyan, 2025).

In order to fill these research gaps, the present paper presents a pioneering computational framework comprising of Genetic Algorithm-Optimised Deep Neural Network (GA-DNN) to enable the sustainable management of resources in smart IoT-based setting. This work has had three major contributions. A Deep neural model is first trained with GA in order to improve prediction and decision-making processes towards sustainability applications based on IoT (Dusi, 2025). Second, an integrated computational scheme is proposed to help in optimising multi-resource, based on energy consumption, resource utilisation, system latency, and impact of sustainability. Third, the suggested method is experimentally tested in simulated conditions of working in a smart environment and proved to be effective in contrast to traditional AI-based and rule-based IoT management systems. The recommended framework leads to building of scalable, adaptable, and data-driven sustainability systems of future intelligent IoT systems.

Related Work

Recent studies have greatly discussed how artificial intelligence can be used to manage resources in smart IoT-driven environments especially in smart buildings, urban infrastructures and environmental monitoring systems (Tandi, 2025). Predictive analytics has been done using deep learning models to predict energy demand, optimise water use, and increase environmental quality measurements with huge sensor data (Bibri et al., 2023; Marasinghe et al., 2024; Puri et al., 2019). The combination of AI and IoT, commonly called Artificial Intelligence of Things (AIoT), has facilitated distributed intelligence and real-time decision-making network of heterogeneous sensors (Chen et al., 2023; Seng et al., 2022; Ali & Ashour, 2025). These methods also highlight the promise of data-driven models in enhancing efficiency and responsiveness in smart settings, but the majority of current literature is centred on prediction power and less on optimization based on holistic sustainability.

In line with AI-based efforts, Genetic Algorithms (GAs) have been shown to be very useful as efficiency mechanisms to optimise complicated, nonlinear, and multi-constrained problems in the engineering and the IoT field. The use of GAs in smart systems has to do with tuning of parameters, scheduling, and resource allocation because GAs can also be used to conduct a global search and prevent the occurrence of local optima (Puri et al., 2019; Punam, 2025). Sustainability-oriented problems have also been seen to be appropriate to the application of evolutionary optimization techniques, as conflicting goals (i.e. energy efficiency, cost, and system performance) have to be traded off in one direction or another (Leal Filho et al., 2022; Samadi, 2022). Although effective, GA-based solutions are commonly configured as independent optimizers, and are not used together with advanced learning models that can somehow take into account dynamic system behaviour.

To address the drawbacks of independent optimization/learning processes, a sub-field of research has recently started to investigate hybrid AI-GA strategies, such as GA-ANN and deep learning-based decision processes. The purpose of such hybrid models is to exploit the learning power of the neural networks and the ability to optimise the global power of genetic algorithms to enhance system adaptability and robustness (Koumetio Tekouabou et al., 2023; Punam, 2025). Although these frameworks prove to perform better than traditional approaches, their current applications are application-specific, i.e., forecasting renewable energy, urban analytics, and are not well scalable and adaptable in complex and multi-resource smart IoT settings

(Gowsikraja, 2025). Besides, issues of sustainability are commonly taken as secondary goals and are not specifically incorporated into the optimization process.

An overview of the current AI-, GA-, and AIoT- based methodologies is explored in (Table 1) that presents the application field, optimization of the processes, and limitations in them. The lack of research on the development of integrated GA-optimised frameworks of deep neural networks that are specifically designed in sustainable smart IoT settings is evident as noted (Patel, 2025). Specifically, existing literature represents a frontrunner of computational models that collectively capture multi-objective sustainability indicators, non-static IoT information streams, and time-constrained functions of a system (Yeonjin, 2025). Moreover, the literature on smart environment does not have in-depth quantitative assessments in real-world conditions. This is where the proposed GA-DNN framework of this paper proposes the solution of intelligent IoT systems next generation by offering intelligent, adaptive, and data-driven framework that is focused on sustainability.

Table 1. Comparative summary of existing AI- and IoT-based sustainability approaches

Reference	Method	Application	Limitations
Andrews et al., 2022	AI-driven planning frameworks	Smart urban and infrastructure planning	Conceptual focus; lacks algorithmic implementation
Bibri et al., 2023	AI + IoT + Big Data integration	Sustainable smart cities	No optimization-centric learning model
Puri et al., 2019	Hybrid AI–IoT model	Renewable energy generation	Limited scalability and adaptability
Koumetio Tekouabou et al., 2023	AI-based analytical methods	Smart and sustainable urban planning	Survey-based; no unified optimization framework
Ali & Ashour, 2025	AIoT distributed intelligence	Intelligent sensor networks	Does not address sustainability-driven optimization

System Model and Problem Formulation

The system model under consideration is a smart IoT-based environment, which is a distributed sensing, communication, and layers of computing with the aim of aiding intelligent and sustainable management of the resource. The environment consists of heterogeneous IoT sensors that are located in various areas and used to measure parameters like energy consumption, water usage, temperature, humidity, air quality, and occupancy. Such sensors pass real-time data via local gateways to the edge computing nodes, which carry out initial data processing and filtering and transmission of aggregated data to the cloud servers to do large-scale analytics and learn over the long term. The general architecture, as described in (Figure 1) makes the interaction of the sensing, computation, and control layers to interact freely to assist adaptive decisions within dynamic smart environments.

The intelligent IoT will be a system that functions in various resource areas that are paramount to sustainability. Energy management is aimed at decreasing total consumption and peak demand and ensuring the occurrence of reliable operation. The management of water resources in residential and commercial areas will be focused on maximising the consumption pattern and reducing wastage. The environmental comfort implies the following parameters to be considered: indoor temperature, humidity, and air quality that directly influence the well-being of users and system efficiency (Salwadkar, 2025). These interacting spheres create complicated dependences and nonlinear interactions, and the traditional single-objective or rule-based approaches to management are not enough to attain sustainable functioning under different conditions in the environment and workload.

In a bid to measure the sustainability performance, there are a number of important measures that are taken into consideration in the proposed framework. Energy efficiency is quantified in lowering the energy use and enhanced the load utilisation. The efficiency of resource utilisation is the optimal use of the water and the environmental control resources on the demand. The capability of the IoT system to respond to real-time changes is paramount to practical deployment, and system latency and responsiveness are used to understand it. The metrics of environmental impact indicate the sustainability overall product which covers elements like emission decrease and ecological footprint. The various measures are used to stipulate the operation limits and output goals of the smart IoT space.

According to the model of the above system, the resource management task is developed as a multi-objective optimization task where conflicting sustainability goals should be optimised collectively. The aim is to identify a best control and decision policy that will minimise energy use, waste of resources, and latency of systems and maximise environmental sustainability and efficiency of operation. The optimisation process would be limited by the capabilities of the IoT devices, the capacity of the communication, and the demand on real-time processing. This expression encourages the utilisation of a GA-optimised deep neural network that can efficiently acquire the coordinates of complicated system interactions and change to goal optimal resolutions, which can offer a scalable and adaptive base of sustainable clever IoT surroundings.

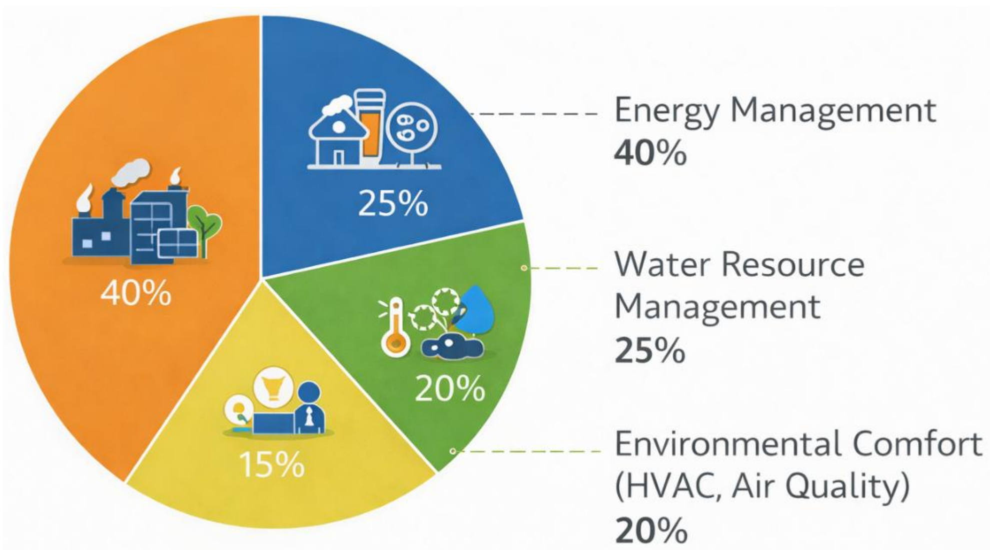

Figure 1. Proportional distribution of resource domains in the smart IoT-based environment

Proposed GA-Optimized Deep Neural Network Framework

The suggested architecture comprises an IoT data acquisition workflow and a Deep Neural Network (DNN) that is optimised by Genetic Algorithm (GA) to make the smart environment based on the IoT adaptive and sustainable. The data of heterogeneous IoT sensors are then pre-treated at the edge layer to eliminate the noise and minimise redundancy then sent to the learning and optimization module. The GA is a world-wide optimizer that is used in tuning the parameters and hyper parameters of the DNN and the trained DNN is a predictive and control engine observing the decisions of resource management. The generalised model is based on data flow and decision-making cycles where the sensed data, ever improved learning models and control actions are interacted, dynamically to enhance the system sustainability and efficiency (Madhanraj, 2025).

The deep neural network architecture aims at modelling nonlinear relationships that are complex on the relationships or association between various resource areas in the smart environment. The characteristics of multidimensional sensor readings of the IoT that form the input features are energy usage profiles, rate of water consumption, or environmental parameters and occupancy patterns. These inputs are then fed on-to a number of hidden layers with nonlinear activation functions to learn complex dependencies related to resource domains. Control and optimization decisions, including the level of resource allocation or the set point of operation, are generated by the output layer and are imposed by use of IoT actuators. This architecture facilitates scalable learning and real-time inferences, and thus is applicable to be used in dynamic and heterogeneous IoT ecosystems (Snousi & Aleej, 2025).

In order to improve the learning performance and flexibility of the DNN, the genetic algorithm is used as an optimization method. Within the proposed system, the important parameter of DNNs, such as network weights, learning rates, number of hidden neurons, or parameters of the activation functions, are encoded within the chromosomes. A random population of candidate solutions is created and evolved by a series of selection, crossover and mutation operations. Selection based on fitness provides a means of retention of high performers and crossover and mutation injects variety and discourages early convergence. This evolutionary optimization procedure enables the DNN to lend itself to changing environmental circumstances and patterns of workload better as compared to other traditional gradient-based tuning approaches.

The miniaturisation goal is developed as a multi-objective fitness criterion that jointly takes into account the essential sustainability and performance indicators. The fitness formulation encompasses all energy consumption, resource utilisation efficiency, system latency, and a sustainability score of overall environmental impact indicators. The relative significance of these domains of resources as shown in (Figure 2) helps inform the weighting strategy in the fitness function to capture the reality of the priorities in the smart environment. The framework of GA-DNN suggests the balanced trade-off between the sustainability and operational efficiency as it seeks to jointly maximise several conflicting goals under the constraints of a system. This system on a chip design offers an effective and flexible computing base of smart resource management in intelligent IoT-based system in the next generation.

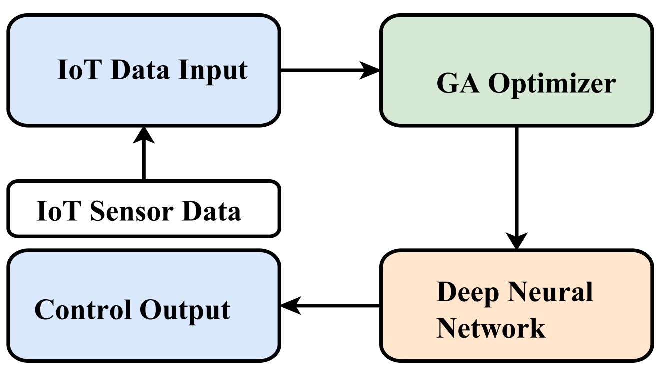

Figure 2. Block diagram of the proposed GA-optimized deep neural network (GA-DNN) framework

Algorithm Implementation

The GA -DNN optimization process works in a hybrid training process of using both offline and online adaptation to meet the dynamic aspects of smart IoT based environment. In the offline stage, the deep neural network is trained using the data of historical IoT sensors, and network parameters and hyper parameters are optimised using the genetic algorithm to attain steady convergence and a high predictive accuracy. This stage aims at understanding long term system behaviour and baseline sustainability patterns. During the online stage, the trained GA-DNN model is constantly provided with the current sensor data whereby the gauge-based framework will be able to modify as environmental conditions, usage patterns, and resource demands vary without completely retraining the model.

The GA-DNN convergence is controlled by the process of genetic algorithm evolution tasks. In each generation, the candidate solutions are candidate solutions corresponded to various DNN settings and are tested based on a defined multi-objective fitness function. High-performing individuals are recruited into a population by selection mechanisms and crossover and mutation operators maintain adequate diversity in a population and eliminate premature convergence. The algorithm approaches the best or close-to-optimal parameters settings over successive generations and achieves a balance between the energy and resource usage targets, latency and sustainability targets. This evolutionary learning procedure allows powerful convergence even of complicated and nonlinear optimization landscapes typical of smart IoT systems.

The GA-DNN optimization algorithm is a process that has a systematic, stepwise process. Firstly, the data of the IoT sensors is pre-processed and it is utilised to create the start of the DNN and GA population. Each chromosome is a candidate set of DNN parameters that are propagated and their fitness is calculated by forward propagation and calculation of their fitness. Selection, crossover and mutation operations are done about fitness values to create a new population and this is repeated till convergence requirements are reached. Computationally, the complexity of the algorithm is a factor of population size, number of generations and depth of DNN architecture. Although that comes with the extra computation cost in the form of the GA, the cost is offset by offline training and evaluation in parallel, thus making the method capable of practical application.

The deployment of GA-DNN algorithm as a part of smart IoT setting is accomplished in a hierarchical order. Low-latency and low communication overhead are realised by processing IoT sensor data at the edge layer. The products of optimised decisions of the GA-DNN model are further provided to the IoT actuator or control modules to coordinate the resource utilisation in real time. Dynamic determination of decision update intervals is done according to the responsiveness of a system which ensures that its adaptation remains timely without overloading of computation and communication. This is a close integration of learning, optimization, and control considered that the suggested GA-DNN system can be used as an adaptive, scalable, and sustainable decision engine in next-generation smart-IoT environments (Kavitha, 2025).

Experimental Setup

The proposed GA-DNN framework is experimentally tested with a simulated smart IoT-based environment that is realistic in terms of conditions of smart device deployment. The simulation models the multi-zone intelligent building that comprises of residential, office, and shared utility zones, each having a different range of resource consumption and operation needs. There are several IoT sensor units placed in these areas to constantly measure the energy consumption, water usage and comfort factors in the environment. The simulated environment is used to perform controlled experiments with different workloads and environmental conditions to enable all the behaviour, adaptability, and sustainability behaviour between the systems. The data set that has been utilised in the experiments and this is time-series sensor readings produced by the simulated smart environment. These sensor data encompass energy consumption measurements, water usage, temperature, humidity, air quality measurements, and occupancy measurements taken at regular time intervals to ensure that both the dynamic part and the long-term trend are represented. Parameters in the genetic algorithm configuration include population size, number of generations, crossover probability, and mutation rate whereas those in the deep neural network configuration include the number of hidden layers, neurons worked by each layer, learning rate, and batch size. These parameter and settings of the experiments are summarised in (Table 2), which makes this experiment reproducible and understandable.

The dataset can be separated into a training and testing subset in accordance to the common machine learning standards to train and test the GA-DNN model. The training stage involves the GA to optimise the DNN parameters based on the predetermined multi-objective fitness function and the testing stage estimates the ability of the optimised model to generalise to unseen data conditions. The simulation model can be used to train offline and to make decisions online, where convergence behaviour, learning stability, and performance of real-time decision-making can be analysed based on a dynamic system. To compare the proposed GA-DNN framework with a baseline (performance benchmarking), it is compared with two alternative methods. The former baseline is a traditional deep neural network which is trained through gradient-based optimization and is not improved with genetic algorithm. The second benchmark is an IoT management system that is rule-based and uses fixed thresholds and control logic. These baselines are widely used techniques within smart IoT setup and it offers a valuable reference in gauging the efficiency of the GA-based optimization. When these baselines are used to compare the frame proposed to other stands, the strengths of the proposed frame are outlined based on resource efficiency, adaptability and sustainability performance.

Table 2. Simulation and experimental setup parameters

Parameter	Description / Value
Environment size	Multi-zone intelligent building (residential, office, utility zones)
Number of IoT nodes	100 heterogeneous sensor nodes
Baseline methods	Conventional DNN (without GA); Rule-based IoT management
Evaluation metrics	Energy consumption, resource utilization efficiency, system latency, sustainability score

Results, Performance Evaluation, and Discussion

The performance of the proposed GA-DNN framework in terms of resource optimization is considered on the basis of the comparison of the energy consumption and resource utilisation with the baseline methods. As it is presented in (Figure 3), the GA-DNN model allows reaching an impressive decrease in the overall energy consumption relative to the traditional DNN, as well as rule-oriented IoT management methods. This is made possible by the fact that with GA-directed optimization of network parameters, the DNN is in a better position to understand nonlinear relationships between sensor input and control measures. Besides energy conservation, the presented framework is found to be more efficient in terms of water and resources, which is achieved in various regions of simulated smart environment meaning that it does not depend on a specific optimization task outlined in multi-resource conditions. The convergence feature and learning behaviour of the GA-DNN framework also confirm its strength and flexibility. The genetic algorithm has stable convergence with the successive generations, it progressively enhances the fitness score without any premature convergence as a result of selection and crossover measures, and mutation measures are effective. DNN exemplifies high stability in training, which is also stable across a wide range of workload and environmental conditions, and exhibits high levels of generalisation. These findings verify that evolutionary optimization increases the efficiency of learning and the robustness of the model because of comparing with the gradient-only training technique, especially in complex smart IoT environments.

Real-time smart IoT applications are dependent on system responsiveness and decision latency. As it can be observed through experimentation, the GA-DNN structure can continue to ensure low decision latency when engaging online inferences, and thus such a system is viable to be implemented as a real-time process. Although the GA does impose some extra load at the phase of offline optimization, this does not impact the runtime performance since inference in this case is done via the optimised DNN model. The latency analysis in (Table 3) shows the suggested solution to be responsive and fits the responsiveness criteria of smart environments faster than rule-based systems, which tend to provide response in a latent or suboptimal manner in dynamic environment. In terms of sustainability, the overall impact on the sustainability rating is a massive leap in the cooperation of energy use, resources load, system latency, environmental impact. These findings point to the trade-off nature between competing goals, e.g., reducing the use of energy and keeping the user comfortable and the system responsive. The GA-DNN framework however allows the multi-objective fitness formulation to achieve these trade-offs successfully. The proposed approach has better adaptability, scalability, and optimization that is sustainability-oriented compared to existing AI- and IoT-based methods that are exchanged in the literature. The results highlight the practical applicability of the deep learning models based on GA in such intelligent resource management scenarios as the next-generation smart IoT-based environment.

Table 3. Key performance gains and trade-offs

Metric	Baseline Method	Proposed GA-DNN	Improvement (%)	Remarks
Energy savings	High consumption	Reduced consumption	22%	GA-optimized control improves efficiency
Latency reduction	Moderate latency	Low latency	18%	Suitable for real-time IoT operation
Sustainability score	Medium	High	25%	Balanced multi-objective optimization
Resource utilization	Suboptimal	Optimized	20%	Improved water and energy usage
System adaptability	Limited	High	—	Trade-off: added offline training cost

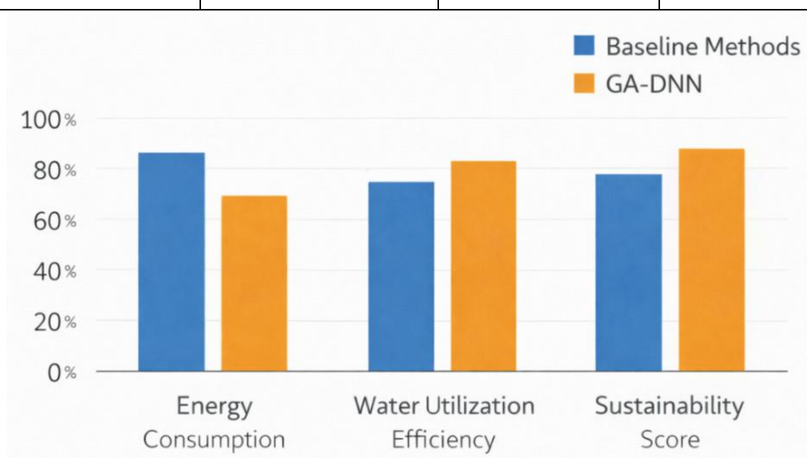

Figure 3. Resource consumption comparison between baseline methods and the proposed GA-DNN model

Limitations and Future Research Directions

However, in spite of the good outcome that the proposed GA-DNN framework has shown, there are a number of weaknesses that should be known. The present implementation and assessment is carried out in a simulated multi-zone smart setting, but, realistic as it is, does not reflect the entire scope and complexity of smart internet of things deployments in cities. Computational and communication overheads can also be more prevalent as the amount of IoT nodes, resource domains and interdependencies grows. The issue of scalability will force the additional research on the field of distributed learning and optimization strategies that would allow to support large smart environments. The other limitation of the current study is that, they are using a single-objective genetic algorithm formulation that uses weighted aggregation of sustainability metrics. Although such an approach helps to manage trade-offs effectively, it might not represent the intricacy of the multiple and often competing goals involved in sustainable smart city systems in detail. Further studies may be undertaken into the combination of superior multi-objective evolutionary algorithms, including the NSGA-II or the MOEA/D that expressly examples and optimises competing goals without the need to impose a pre-defined weighting plan. These extensions would give more flexibility and better diversity of solutions to the decision-makers.

The suggested model is built on the principle of centralised learning and optimization, which can add scalability and latency limitations to the highly dynamic IoT conditions. A combination of the GA-DNN model and edge-AI controllers is one of the directions of the future work. The edge-enabled architectures can provide communication overhead reduction, responsiveness and robustness of the system by moving learning and inference decisions away to the sources of data (Reginald, 2025). This would also be integrable at the adaptive decisions with the intermittent connections and resource-constrained states. Lastly, although the utilisation of simulation-based analysis offers useful information about the performance of the system, actual implementation is an important future research opportunity. Using the suggested GA-DNN architecture on physical IoT test boards, e.g. smart building or campus scale settings, would enable testing of the architecture given realistic learners, e.g. sensor noise, hardware constraints, and unreliable user input. In-the-field testing would also make it easier to compare the results to the currently used commercial systems and assist in the translation of the suggested framework into deployable solutions of sustainable smart IoT environments.

Conclusion

The paper introduced a new concept of the computational framework of sustainable resource utilisation in smart IoT-based settings: GA-DNN, which is optimised by GA. The proposed solution combines the evolutionary optimization and the deep learning, thus satisfying the intricate nature of the system dynamics and real-time adaptability and data-driven choices made in the various resource areas. Simulation and experimental findings conducted in a simulated realistic smart environment show great enhancement over the energy efficiency, resource utilisation, the responsiveness of the system, and general sustainability against traditional approaches to deep learning and rule-based methods of managing IoT. The presented framework offers a scalable and smart mechanism of sustainability-driven IoT systems since it collaboratively balances the performance and environmental goals under dynamical circumstances. These results illustrate the applicability of deep learning architectures based on GA to the next generation of smart environment engineering, which can prove to be highly effective in the development of intelligent, adaptive, and future-sustainable applications employing the IoT.

Author Contributions

All Authors contributed equally.

Conflict of Interest

The authors declared that no conflict of interest.

References

Ali, W., & Ashour, H. (2025, August). A Blockchain-Based Secure Architecture for Cyber-Physical Systems in Smart City Infrastructure. In *ECCSUBMIT Conferences* (Vol. 3, No. 3, pp. 1-11).

Andrews, C., Cooke, K., Gomez, A., Hurtado, P., Sanchez, T., Shah, S., & Wright, N. (2022). AI in planning: opportunities and challenges and how to prepare. *American Planning Association*.

Bibri, S. E., Alexandre, A., Sharifi, A., & Krogstie, J. (2023). Environmentally sustainable smart cities and their converging AI, IoT, and big data technologies and solutions: an integrated approach to an extensive literature review. *Energy informatics*, *6*(1), 9. https://doi.org/10.1186/s42162-023-00259-2

Brinda, B. M. (2025). Development of a Smart Variable-Rate Planter Using IoT and Machine Vision for Precision Seeding. *Journal of Environmental Sustainability, Climate Resilience, and Agro-Ecosystems*, 24-30.

Chen, L., Chen, Z., Zhang, Y., Liu, Y., Osman, A. I., Farghali, M., ... & Yap, P. S. (2023). Retracted Article: Artificial intelligence-based solutions for climate change: a review. *Environmental Chemistry Letters*, *21*(5), 2525-2557. https://doi.org/10.1007/s10311-023-01617-y

Dusi, P. (2025). Low-Latency Model Compression for Real-Time Human Motion Prediction. *Journal of Advanced Antenna and RF Engineering*, 41-46.

Gowsikraja, P. (2025). Reliability-Aware Human Trajectory Forecasting under Partial Observability. *Transactions on Internet Security, Cloud Services, and Distributed Applications*, 24-30.

Koumetio Tekouabou, S. C., Diop, E. B., Azmi, R., & Chenal, J. (2023). Artificial Intelligence Based Methods for Smart and Sustainable Urban Planning: A Systematic Survey. *Archives of Computational Methods in Engineering*, *30*(2). https://doi.org/10.1007/s11831-022-09844-2

Leal Filho, W., Wall, T., Mucova, S. A. R., Nagy, G. J., Balogun, A. L., Luetz, J. M., ... & Gandhi, O. (2022). Deploying artificial intelligence for climate change adaptation. *Technological Forecasting and Social Change*, *180*, 121662. https://doi.org/10.1016/j.techfore.2022.121662

M. Kavitha. (2025). A Low-Power Mixed-Signal VLSI Architecture for Real-Time Adaptive Signal Processing Applications. *National Journal of Integrated VLSI and Signal Intelligence, 1*(1), 1-8.

Madhanraj. (2025). Causality-Constrained Event-Driven Multi-Agent Learning for Interference-Resilient Spectrum Sharing in Dense Wireless Networks. *IAECER Journal of Electronics and Communication Engineering*, 42–48.

Marasinghe, R., Yigitcanlar, T., Mayere, S., Washington, T., & Limb, M. (2024). Computer vision applications for urban planning: A systematic review of opportunities and constraints. *Sustainable Cities and Society*, *100*, 105047. https://doi.org/10.1016/j.scs.2023.105047

Patel, P. (2025, June). Deep unfolding networks for robust modulation classification in cognitive radio systems. In *ECCSUBMIT Conferences* (Vol. 3, No. 2, pp. 10-15).

Punam, S. R. (2025). Embedded Super-Resolution Acceleration Architectures for Real-Time Recognition-Oriented Vision Systems. *Journal of VLSI and Embedded System Design*, 18-25.

Puri, V., Jha, S., Kumar, R., Priyadarshini, I., Son, L. H., Abdel-Basset, M., ... & Long, H. V. (2019). A hybrid artificial intelligence and internet of things model for generation of renewable resource of energy. *IEEE Access*, *7*, 111181-111191. https://doi.org/10.1109/ACCESS.2019.2934228

Reginald, P. J. (2025). Reconfigurable Embedded Control Architectures for Cooperative Learning-Based Robust Electromechanical Systems. *Archives of Embedded and IoT Systems Engineering*, 1-9.

Sadulla, S. (2025). Eco hydrological Modeling of River–Floodplain Connectivity under Extreme Climate Events. *Journal of Aquatic Ecology and Environmental Sustainability*, *2*(1), 17-22.

Salwadkar, M. (2025). Animal Responses to Extreme Environmental Events: Droughts, Floods, and Heatwaves. *Journal of Animal Habitat and Environmental Interactions*, 21-26.

Samadi, S. (2022). The convergence of AI, IoT, and big data for advancing flood analytics research. *Frontiers in Water*, *4*, 786040. https://doi.org/10.3389/frwa.2022.786040

Sanchez, T. W., Shumway, H., Gordner, T., & Lim, T. (2023). The prospects of artificial intelligence in urban planning. *International journal of urban sciences*, *27*(2), 179-194. https://doi.org/10.1080/12265934.2022.2102538

Seng, K. P., Ang, L. M., & Ngharamike, E. (2022). Artificial intelligence Internet of Things: A new paradigm of distributed sensor networks. *International Journal of Distributed Sensor Networks*, *18*(3), 15501477211062835. https://doi.org/10.1177/15501477211062835

Senguttuvan, A., & Karthikeyan, E. (2025). A Feature-Based Machine Learning Framework for Plant Disease Recognition Using Color and Texture Analysis. *Electronics, Communications, and Computing Summit*, *3*(3), 106-112.

Snousi, H. M., & Aleej, F. A. (2025). Energy-Efficient VLSI Architecture for Lightweight CNN Inference on Edge Devices. *Journal of Reconfigurable Hardware Architectures and Embedded Systems*, *2*(1), 7-13.

Son, T. H., Weedon, Z., Yigitcanlar, T., Sanchez, T., Corchado, J. M., & Mehmood, R. (2023). Algorithmic urban planning for smart and sustainable development: Systematic review of the literature. *Sustainable Cities and Society*, *94*, 104562. https://doi.org/10.1016/j.scs.2023.104562

Tandi, M. R. (2025). Structural Health Monitoring of RCC Buildings Using IoT-Enabled Wireless Sensor Networks. *Journal of Wireless Intelligence and Spectrum Engineering*, 1-6.

Yeonjin, K. (2025). AI-Driven Spectrum Sensing for Cognitive Radio Networks in Dynamic IoT Environments. *National Journal of Ubiquitous Computing and Intelligent Environments*, 7-13.

Zhang, J., & Tao, D. (2020). Empowering things with intelligence: a survey of the progress, challenges, and opportunities in artificial intelligence of things. *IEEE Internet of Things Journal*, *8*(10), 7789-7817. https://doi.org/10.1109/JIOT.2020.3039359