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An Intelligent IoT-Driven Smart Environment Framework Using Genetic Algorithms and Neural Computing for Sustainable Resource Management

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Abstract

The rapid adoption of Internet of Things (IoT) development has created the possibilities of smart environments that can maintain constant monitoring and smart control of the vital resources. Nevertheless, traditional rule based and fixed optimization methods tend to be rigid to dynamic and heterogeneous environments in the real world and result into inefficient use of resources and higher energy use. To offer solutions to these issues, the paper is proposing the implementation of an intelligent IoT-enabled smart environment framework to bring neural computing in conjunction with a Genetic Algorithm (GA)-based optimization plan to sustainable resource management. Under the suggested model, the IoT sensors would receive real-time data about the environment in which they are installed and the way they are used, which

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are then processed by a neural computing unit to forecast resource demand trends. A GA in turn uses these predictions to make adaptive optimization of the allocation of resources under a variety of sustainability and operating constraints. The fitness function used by the GA reflects a combination of energy efficiency, usage of resources, and comfort to the user and it allows making strong decisions in dynamic environments. The experimental testing done on a simulated smart environment shows that the suggested framework will considerably decrease the consumption of the resources and enhance the general sustainability of the process as compared to the traditional non-optimised and heuristically-driven techniques. The findings confirm the usefulness of the evolutionary optimization strategy along with the use of neural intelligence that structured the adaptive, energy-efficient IoT-based smart environments, and they demonstrate that the framework can be implemented in the next-generation sustainable architecture of infrastructure systems.

Keywords:

IOT, smart environment, genetic algorithm, neural computing, sustainable resource management, intelligent optimization.

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Introduction

Smart environments have become one of the main prerequisites of meeting the sustainability targets in the contemporary city and infrastructural framework due to increased pressure on efficient use of energy, minimum waste utilisation, and better living standards. The accelerated urbanisation and climate change factors have enhanced the necessity of smart systems which are capable of handling resources including, energy, water and services pertaining to the environment in an efficient and adaptive mode. Smart cities, buildings and ecosystems take advantage of the developed sensing, communications and control technologies to survey the environmental conditions and human behaviour in real-time, hence making smart decisions on how to operate sustainably (Batool et al., 2021; Fong et al., 2017; Mohanty et al., 2016). Nevertheless, the growing sophistication and flux of these environments is a great challenge to traditional management strategies.

Internet of Things (IoT) is a significant aspect in the achievability of smart environment as it offers real-time and continuous data capture over a heterogeneous network of sensors and mobile devices. IoT-based designs can facilitate an easy combination of environmental sensors, smart metres, wearable and smart appliances to facilitate real-time monitoring and control (Mohanty et al., 2016; Sindhu, 2024; Sung et al., 2019). Such data streams are used to support modern analytics in applications e.g., energy, HVAC control, traffic, and irrigation control (Mistry, 2022; Abi Saab et al., 2019; Saleem et al., 2022). In spite of these improvements, the successful use of IoT data in intelligent decision-making is still a challenge because the volume, variability and uncertainty of the environment are incomprehensible in reality.

The conventional methods of managing resources in smart environments include rule-based approaches to control or statical optimization methods that are not scalable or open to changes. These approaches do not usually react well to dynamic variations in the environmental conditions, user behaviour and availability of resources, leading to inefficient performance and unnecessary wastage of resources (Papazoglou & Biskas, 2023; Veerappan, 2025). Although heuristic and mathematical optimization methods have been discussed, they are not always successful in dealing with nonlinearity, multi-objective limitation, and real-time flexibility. Recent works have also suggested the promise of evolutionary and swarm-based optimization methods on energy and resource management, but there are numerous existing methods that do not either include learning-based models or specifically lack predictive intelligence; furthermore, most existing methods do not include learning-based models of proactive control (Ibrahim et al., 2024; Meng & Li, 2024).

In a bid to overcome these shortcomings, in this paper, a smart environment framework grounded on IoT is suggested that will merge neural computing with Genetic Algorithm (GA) on optimization of resources to be sustainable. In the suggested system, neural computing models will be used to predict patterns of resource demand based on real-time data of IoT sensor data, and the GA will be used to conduct adaptive costing of resources allocation due to sustainability and operating constraints. The key findings here are: (i) a single architecture, based on the IoT and driven by smart environments, is designed, (ii) the incorporation of the GA to drive the optimization of efficient and adaptive resources, (iii) the inclusion of the neural computing to predict demand and make intelligent control decisions, and (iv) the performance evaluation aims at sustainability, efficiency and effectiveness of optimization. The suggested strategy shows how integrating evolutionary optimization and neural intelligence would facilitate the provision of next-generation sustainable smart environments.

Related Work

The recent years have observed the intensive research aimed at creating the IoT-enabled smart environment and smart city schemes to enhance the sustainability, efficiency, and quality of life. It has been highly known that IoT forms the foundation of smart environments, a place through which mass sensing, communications, and real-time data collection takes place across all areas of application (Mohanty et al., 2016). Other researches have suggested IoT-based platforms of smart homes, buildings, and cities, with the emphasis on automation and centralised control through cloud computing platforms and mobile applications (Mistry, 2022; Sindhu, 2024). Also, smart traffic regulation, smart irrigation, and environmental observation have shown that IoT can be used in the control of the complex urban infrastructure (Abi Saab et al., 2019; Saleem et al., 2022). The general characteristics and typical IoT-based smart environment frameworks are summarised comparatively in (Table 1).

The response to resource management within the IoT-enabled set up has been checked fully especially in the towards energy efficiency, load balancing, and consumption modelling. Predicting energy consumption and tuning operations of smart buildings and low-energy systems have been done using machine learning and data-driven techniques (Veerappan, 2025; Kumar, 2025). Other works are on appliance-level modelling and usage-profiling to aid demand-side management, whereas others are on decision-support systems to make real-time control (Poornimadarshini, 2025). Irrespective of these developments, most of the current resource management solutions are based on fixed policies or thresholds and this restricts their ability to adapt to the dynamic environmental environments and user activity (Papazoglou & Biskas, 2023; Fu & Zhang, 2025). This leads to a real concern of having smart and responsive optimization system able to accommodate real time dynamism in the IoT systems (Lim & Lee, 2025).

Genetic Algorithms (GAs) and evolutionary optimization methods have extensively been used on complex optimization problems of energy and resource management since they embrace the ability to address nonlinear, multi-objective, and limited search space (Mukti, 2025). It has been demonstrated that GAs can be used to solve optimal power flow and energy management problems more efficiently than traditional optimization and heuristic techniques do (Papazoglou & Biskas, 2023). Other recent studies have also considered methods to optimise the convergence and quality of solutions of hybrid optimization methods, such as the particle swarm optimization (PSO) and fuzzy-based methods that are based on evolutionary methods (Ibrahim et al., 2024; Meng & Li, 2024). Nevertheless, a number of these strategies are centred on maximisation rather than forecasting intelligence thus limiting their capacity of responding proactively to future demand trends to smart environments.

Table 1. Summary of related work on iot-based smart environments and optimization techniques

Ref.	Application Domain	Technique Used	Key Contribution	Limitation
Mohanty et al., 2016	Smart cities	IoT-based sensing and communication	Established IoT as the backbone of smart city infrastructure	Lacks intelligent optimization mechanisms
Batool et al., 2021	Smart ecosystems	Artificial Neural Networks (ANN)	Intelligent modeling of environmental systems	No optimization-driven resource allocation
Papazoglou & Biskas, 2023	Energy systems	Genetic Algorithm (GA), PSO	Comparative analysis of evolutionary optimization methods	Focused on power flow only
Veerappan, 2025	Smart buildings	Machine learning-based prediction	Accurate energy consumption forecasting	Static control policies
Ibrahim et al., 2024	Energy management	Fuzzy logic–PSO optimization	Integrated storage-aware energy management	Limited neural prediction integration

Techniques of neural computing and artificial neural networks (ANN) and deep learning models have been proven to be very strong in modelling the environment, pattern recognition and predicting demand in smart ecosystems (Batool et al., 2021; Veerappan, 2025; Punam, 2025; Maria et al., 2025). These models allow historical and real-time IoT data to be used to learn about energy consumption, environment, and behaviour of the system. However, the current researches tend to separate prediction and optimization and provide with fragmented solutions. Based on the overview of (Table 1), it can be observed that there is a cavernous gap in the literature regarding a seamless operation between the GA-based optimization and neural computing in the context of IoT-based sustainability. More to the point, there is a scarcity of adaptive multi-objective optimization methods that would aim at achieving efficiency, sustainability and user comfort in a unified manner, which drives the proposed unified GA -neural computing framework in this paper.

System Overview and Problem Formulation

The proposed smart environment architecture of the IoT is aimed at fostering uninterrupted sensing, smart decision-making and dynamic control of the resource management to handle resources sustainably. The architecture is layered (as shown by (Figure 1)) in that it enables scalability and modularity and provides seamless interaction among the sensing, computation and actuation units. This stratified solution helps to efficiently collect and distribute data between heterogeneous IoT assets and intelligent optimization units and enable bidirectional control mechanisms to engage in real-time and context-specific resource management of smart spaces. The lowest in the line, the system takes into consideration a heterogeneous layer of sensors including environmental sensors, smart energy metres, water flow sensors, occupancy detectors, and smart appliances (Villanueva et al., 2022). These sensors keep tracking the physical conditions of temperature, humidity, energy use, water use, human presence and provide real time streams of data that indicate the dynamic condition of the environment. Data gathered is relayed via the communication layer that comprises of IoT gateways and edge/cloud connectivity that are reliable. This layer guarantees secured and low-latency data transmission and pre-processes at the edge to both lessen communication overheads and make timely decisions.

The intelligence layer and data processing component is the main part of the suggested architecture and is a combination of neural computing and Genetic Algorithm optimization. Neural computing models are used to analyse real-time sensor data and historical sensor data to predict the demand pattern of resources and environmental dynamics. The GA makes use of these predictions to do adaptive optimization of the resource allocation considering various objectives and constraints. The intelligence level tests solutions that have been applied to it based on sustainability-oriented fitness functions and it constantly improves control strategies based on the feedback provided by the environment and in the process proactive and adaptive system behaviour is displayed in (Figure 1). It is on this basis that the resource management problem is defined as a constrained optimization problem with various interdependent resources such as energy, water, HVAC systems and lighting. The major targets are to reduce the total amount of energy consumption, lessen the wastage of the resources, and enhance system sustainability and efficiency during its operations, without compromising the comfort of the user and quality of services. Resource refinements and limitations: The capacity limits of a resource, the comfort levels, the operational safety demands and the real-time responsiveness are a few of the system constraints. The framework introduces resource management as a multi-objective optimization problem in the proposed IoT-driven architecture, which allows implementing intelligent, adaptive, and sustainable management of smart environments.

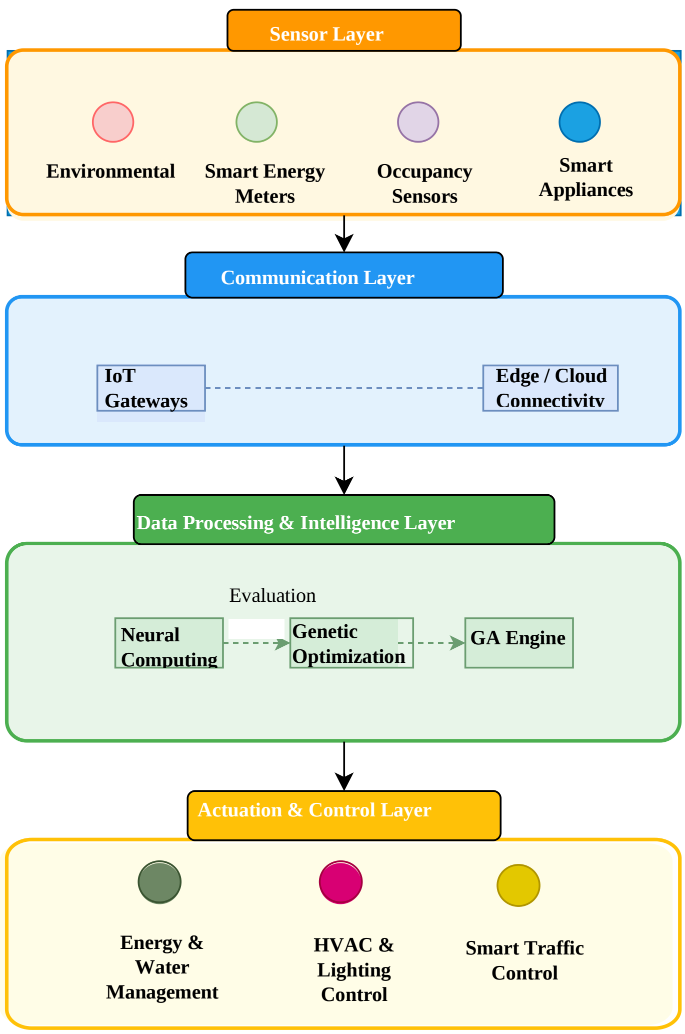

Figure 1. Layered architecture of the proposed iot-driven smart environment for intelligent and sustainable resource management

Proposed Intelligent Framework

It is suggested that the intelligent approach to managing resources in smart environments combines IoT sensing, neural computing, and optimization with the use of Genetic Algorithm to provide adaptive and sustainable resource management. The framework presented in (Figure 2) is a closed-loop operational cycle, which has an initial step of data acquisition by distributed sensors of IoT and the final step of intelligent actuation and feedback. Raw sensor data, the first step in processing, is conducted to eliminate noise, deal with values that have been removed and to standardise heterogeneous inputs. Predictive intelligence and decision-making based on optimization of the system relies on this processed data stream. The main element in the framework is the neural computing module, which predicts future demand of resources and environment adjustments basing on real-time and historical data of the IoT. It uses an artificial neural network (ANN) or a long short-term memory (LSTM) model, depending on the application case, to help formulate nonlinear relations and time dependencies of sensor data. The input features consist of environmental parameters, energy use and water use measures, occupancy measures, and time measures. The neural model produces the predicted demand levels or environmental conditions which are continuously updated using the historical data in order to hone to the correct and sturdy predictions in the dynamic working conditions (Vijayan, 2022).

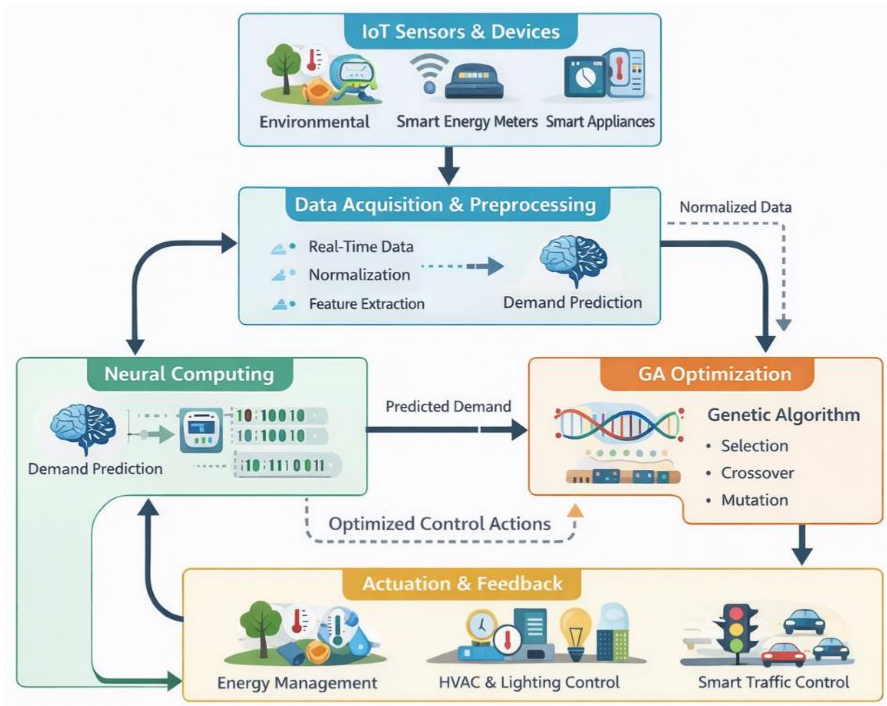

Figure 2. Block diagram of the proposed genetic algorithm–neural computing framework for intelligent iot-based resource optimization

The generated demand forecast data of the neural computing module is then used by the Genetic Algorithm (GA) based optimization engine to calculate the best resource allocation schemes. Under the GA formulation, resources allocation decision is encoded in each chromosome as a candidate solution amongst numerous controllable components. The fitness mandate is aimed at considering the combination of energy efficiency, sustainability indices like minimised resource wastage and emissions, and comfort limitations to the users. The standard GA processes, such as selection, crossover and mutation, are used repeatedly to develop the population into optimum solutions, which allow search space to explore complex and constrained space economically. This optimization is repeated until convergence or termination conditions have been met, e.g. a maximum number of generations has been reached or the value of the fitness has changed insignificantly. After the identification of an optimal solution, the respective control measures are implemented using the actuation layer to govern the use of energy, HVAC operation, lighting intensity among other resources that are being controlled. These actions can be constantly assessed through a feedback loop to take action through IoT sensors so that the framework can adjust to the evolving environmental conditions and user behaviour. Such closed-loop intelligence as illustrated in (Figure 2) generates real time flexibility, enhanced sustainability, and resilient performance of the put forward internet of things based smart environment architecture.

Algorithm Design and Workflow

The suggested algorithm has a closed-loop optimization cycle in which IoT sensor data are constantly being gathered, pre-processed and converted into valuable features that outline the present working condition of the intelligent environment. These characteristics are passed on to the neural computation unit (ANN/LSTM) that forecasts short-term resource requirements (e.g. predicted energy load, water consumption, and hvac demand due to occupants). The forecasted demand is considered a predictive approach that does not entail any reactive control but allows making proactive decisions. This is then the prediction output that is inputted into the Genetic Algorithm (GA) engine to inform the setting of resources and scheduling in a manner that is knowledgeable of sustainability-focused goals.

Optimal allocation of resources based on GA starts by coding a candidate plan of allocation of resources, which is encoded in the form of a chromosome. The chromosomes are possible control settings of the resources that are under control, i.e. HVAC set points, lighting intensity levels, energy distribution priorities, water allocation schedules, and appliance operating times. The starting population of chromosomes may be created randomly, or as a heuristically selected population to provide faster convergence. A fitness score is calculated with a multi-objective formulation of energy efficiency, resource wastage reduction, sustainability (e.g. penalty on excessive consumption) and user comfort constraints, depending on a chromosome. Notably, neural forecasts are already incorporated into the fitness calculation in such a way that candidate solutions can be evaluated on their ability to fit future demand conditions and not only on latest sensor measurements.

Once the computation of fitness is finished, the GA goes through an iterative process of evolutionary optimisation based on the conventional genetic operations. The powerful chromosomes are selected to reproduce with the application of tournament selection or roulette-wheel selection; better solutions have more likelihood of spreading through selection. Crossover is then used to swamp genes between sets of parent chromosomes creating offspring with mixed control decisions allowing exploration of a variety of allocation strategies. Mutation adds controlled randomness through the manipulation of a small fraction of the genes; which prevents a premature convergence, and improves resiliency in dynamic IoT. Each generation, capacity limits and comfort boundaries are imposed in the fitness function by repair functions or penalty terms to make sure that the functions developed during evolution are practical (Vijay et al., 2022).

A workflow is stopped when a convergence or stopping criteria is met, e.g. when the number of generations is greater; when the best-fitness of the solution does not change significantly over a series of iterations; or when the sustainability of the solution reaches a predefined sustainability threshold. The fittest chromosome is subsequently chosen as the most optimal solution and its decoded parameters are converted to control commands that are actuated by the actuation layer (HVAC controllers, lighting systems, energy management units and water control devices). The last step is the validation of the effect of the implemented actions with the assistance of real-time feedback provided by IoT sensors and updating the dataset used to enable further prediction and optimization processes. Such a cyclic process empowers the adaptive and optimization-based regulation that enhances sustainability performance without deteriorating the operational stability and comfort ability of users in intelligent environments.

Experimental Setup

The proposed framework test is performed with the help of an experimental simulation of an IoT-based smart environment which models a typical multi-zone smart building environment. The environment is made up of interrelated spaces in the form of offices, residential houses and shared utility facilities creating a managed smart zone with mixed resource requirements. This test system allows evaluating energy management, water management, HVAC, and lighting management under different occupancy and in different environmental conditions. Virtual IoT sensors used on a network perform this to track variables such as temperature, humidity, energy use, water flow, the presence of occupants and time-of-use profiles and gives realistic and heterogeneous data streams that evoke real-life operating conditions.

The simulated IoT environment is designed and organised to facilitate data collection and communication in a similar way that it employs a gateway-based architecture with edge-to-cloud connectivity. Sampling of sensor data is done and fed to the processing layer where preprocessing methods like normalization, use of noise filters and feature extraction methods are performed. The simulation enables user behaviour and environmental conditions to be varied under controlled conditions and thus assess the robustness of the system. There are also historical sensor data to train the neural computing module and test the demand prediction performance in various scenario operation conditions.

The implemented engine is based on generalised scientific computing and machine learning platforms. The neural computing unit is implemented as an artificial neural network of feed forward or LSTM based on the time complexity of input data and is trained in supervised mode by use of historical sensor data. Genetic Algorithm works on a population-based evolutionary scheme and the parameters are configured based on the following parameters, population size, mutation rate, crossover probability as well as number of generations. The parameters used in the experiment regarding the selected GA and neural network configuration are presented in (Table 2), transparency and reproducibility of the implementation will be ensured.

The different quantitative measures applied to assess system performance are efficiency, sustainability, and computational feasibility. The energy consumption is determined as the sum total of the energy consumed by the managed resources during the simulation time period, whereas the efficiency of resource utilisation indicates the proportion between resource used effectively and the capacity. A sustainability index is determined to measure resource conservation and waste reduction as compared to base-line strategies. Also, additional evaluation is made on computational overhead based on the algorithm execution time, processing load, such that the proposed framework can be implemented in real-time or near-real-time in an environment based on the IoT.

Table 2. Experimental parameters and GA configuration

Parameter	**Description**	**Value**
Simulation environment	Smart building with multi-zone setup	Offices, residential units, utility areas
IoT sensor sampling interval	Data acquisition rate from sensors	5 seconds
GA population size	Number of candidate solutions per generation	50
GA mutation rate	Probability of gene mutation	0.05
Number of GA generations	Maximum optimization iterations	100

Results, Performance Evaluation, and Discussion

The performance of the proposed GA-neural computing structure is optimised with respect to the analyses of the convergence behaviour of the Genetic Algorithm, and the efficiency of the resource allocation. The GA provides convergence which is steady and stable over repeated simulation runs, converging to close-optimal fitness values within very few numbers of generation. This action suggests the exploration and exploitation of the solution space with the assistance of integrating neural demand predictions into the fitness assessment. The convergence curve as shown in (Figure 2) demonstrates that in the initial generations, loss is reducing very rapidly and thereafter the loss reduces gradually, which explains why GA is suitable in complex multicurve resource management problems in dynamic IoT-driven environments. The benefits of sustainability and efficiency that the proposed framework will produce are evaluated by conducting a comparative analysis of the methods that follow the baseline methods, such as rule-based control and static optimization. The findings pin a substantial decrease in total energy usage and wastefulness of resources in case one uses the GA-based framework. The system is more efficient in charges of utilisation by proactively allocating resources that are based on predicted demand versus reactive thresholds, and also, energy, water, HVAC, and lighting subsystems achieved greater utilisation efficiency. The existence of quantitative improvements in performance such as those captured in (Table 3) indicates significant advancement of the sustainability metrics hence the efficiency of evolutionary optimization as a solution to the challenges that are witnessed in the existing non-evolutionary oriented smart environment control strategies, specifically resource inefficiencies (Muralidharan, 2024).

An in-depth comparative scheme also reflects the benefits that the proposed GA-based framework had compared to the traditional optimization methods. The traditional approaches are normally based on predetermined parameters or simplified models hence are not able to respond to time-dependent changes in environmental conditions and human behaviour. Compared to it, the GA-based method adaptively reacts to changes in control choices by an iterative evolution process, making nonlinear constraint and competing goal management opportunities superior. In addition, the integration of neural computing is also associated with high performance of the GA that facilitates the optimization process to solutions that will be operational with future conditions with the operating environment as illustrated by the refined improvement trends indicated by (Figure 3).

In a bigger scale, the findings justify the advantages of GA-based intelligent optimization of scalable and adaptive smart environments. This framework proves highly adaptive to changing environments and resource requirements, which makes it applicable to implementation in massive smart buildings, campuses, or urban areas. The scalability is supported by the modular architecture and closed loop feedback mechanism that would not incur too much over head on the computational part as attested by the efficiency metrics in (Table 3). In practise, the findings indicate that the ability to combine evolutionary optimization with neural prediction can contribute greatly to sustainability, efficiency of operation, and intelligence of the decision making of the next generation of the IoT-enabled smart environment.

Table 3. Key performance gains and trade-offs

Metric	Baseline Method	Proposed GA–Neural Framework	Improvement / Trade-Off
Energy consumption	High	Reduced	Significant energy savings
Resource utilization efficiency	Moderate	High	Improved allocation accuracy
Sustainability index	Low–moderate	High	Reduced resource wastage
User comfort compliance	Fixed thresholds	Adaptive control	Better comfort preservation
Computational overhead	Low	Moderate	Acceptable for real-time use

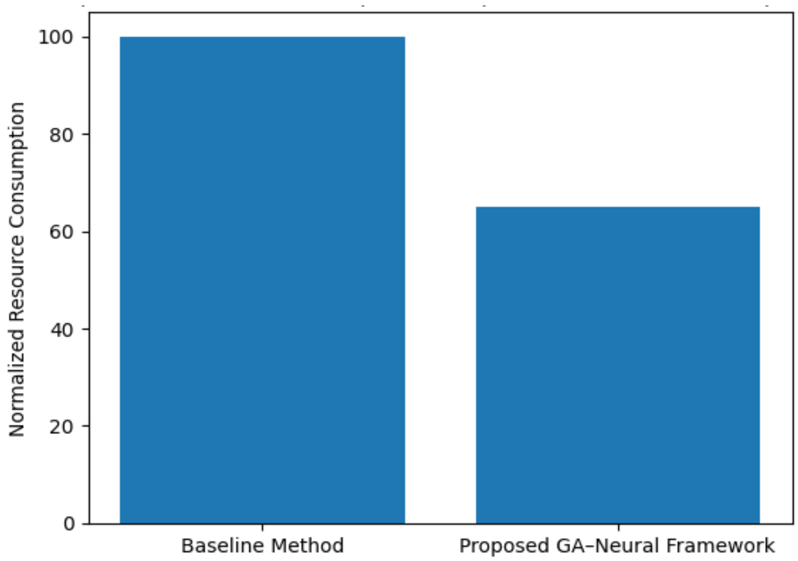

Figure 3. Comparison of resource consumption between baseline method and proposed ga–neural framework

Limitations and Future Research Directions

Although the suggested IoT-based GA comes with a neural computing framework has proven to be promising in its outcomes, there are some restrictions that have to be considered. The assessment is performed in the context of simulated smart environment to represent a multi-zone smart building, and, although the environment is realistic, it fails to reflect the volume and dimension of large smart city infrastructures. With an increase in the number of IoT devices, the resources under its control, and the stakeholders, difficulty in communication latency, the heterogeneity and the coordination of the various components may emerge. A strategy to deal with the issue of scalability is then crucial in extrapolating the proposed framework to the city scale implementations.

The other weakness of the current work is the application of single-objective or aggregate fitness formulation in the Genetic Algorithm. Despite the fact that the fitness function is characterised by the combination of various factors like energy efficiency, sustainability and user comfort, the above objectives are implemented as one optimization criterion. It may be enhanced in future research by using more sophisticated variants of GA like NSGA-II or MOEA-based methods as a means to explicitly represent the trade-offs between competing objectives and produce Pareto-optimal answers. It would allow more flexible and transparent decisions in the situation when priorities differ among applications or among users. The existing framework is also based on neural prediction and GA-based optimization, which is on a centralised or semi-centralised processing. Although such a design eases implementation and assessment, it can make it less responsive in very dynamic systems or ones with other significant latencies. Future extensions may support real-time edge-AI controllers that will do localised prediction and optimization to the sources of data. This intelligence enabled on the edge would minimise overheads on communication, ensure real-time adaptability, and resilience to network disruption during large-scale inputs on IoT adoptions.

Lastly, the suggested framework is mostly confirmed by the means of simulation experiments. Even though the evaluation conditions offered by simulation are controlled and repeatable, real-world test beds in the IoT bring practical considerations to simulation: sensor noise effects, device malf, losses in communication and unexplained user behaviour. The next step in the future will be to apply the framework to actual IoT test bed and pilot installations of smart environments to test robustness, sustainability performance and reliability. These practical applications will be essential in the role of transforming the proposed solution into an actual model in moving past a research prototype version to a viable solution on intelligent and sustainable smart environment on the next generation.

Conclusion

This paper illustrated a smart environment system based on intelligent IoT-controlled frameworks to optimise the adaptive management of resources through neural computing and Genetic Algorithms. Through proactive and control-informed utilisation of real-time, IoT sensor and neural demand prediction, the offered framework is successfully used to control the energy, water, HVAC, and light resources in the dynamic environment. The optimization based on GA showed good convergence characteristics, as well as, large amounts of enhancement in the efficiency of resource utilization and sustainability relative to the traditional rule-based and non-dynamic optimization strategies (Kozlova & Smirnov, 2025; Prasath, 2025). The framework by itself was demonstrated, with the help of extensive experimental assessment, to have less resource consumption and user comfort at reasonable computational overhead. On the whole, this paper offers a scalable and intelligent framework of sustainable smart environmental management and emphasises the applicability of evolutionary optimization and neural intelligence to the next generation IoT-based systems, which target energy efficiency, scalability and long-term sustainability.

Author Contributions

All Authors contributed equally.

Conflict of Interest

The authors declared that no conflict of interest.

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