ISSN: 2458-8989

Natural and Engineering Sciences

NESciences, 2025, 10 (3): 819-832 doi: 10.28978/nesciences.1811162

AI-Enabled Neural Computing and Genetic Algorithm Optimization for Resource-Efficient Smart Environments in IoT Applications

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Abstract

The recent accelerated growth of Internet of Things (IoT) implementations in smart environments has amplified the situation regarding the energy efficiency and computational scalability coupled with dynamic resource management in heterogeneous and timevarying conditions. Old-fashioned centralised and non-adaptive based optimization mechanisms are growing to be ineffective mainly because they are very rigid, and they consume a lot of overhead. In order to overcome these limitations, the given paper will introduce an AI-assisted hybrid optimization strategy which incorporates the principles of neural computing with those of genetic algorithm (GA)-run evolutionary optimization to facilitate resource-optimal and intelligent

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performance of IoT-driven smart surroundings. Under the suggested methodology, lightweight neural computing frameworks implemented at the edge tier offer real-time local awareness and forecast estimation of the workload, energy requirements and network states of affair. A multi-objective GA then uses these predictions to produce dynamic optimization of the critical system parameters such as task scheduling, duty cycling, transmission power and edge-cloud offloading decisions. Closed-loop feedback allows the hybrid neural to act proactively and to implement global optimization and dynamically adapt itself through a hybrid neural structure. Comprehensive simulations of the framework on the basis of different node densities and traffic conditions prove that the proposed framework outperforms the traditional heuristic, neural-only, and GA-only strategies through optimization significantly. Experiments have shown significant energy savings and latency at the end, and significant increases in network lifetime and Quality of service (QoS) sustainability. The solution proposed is scalable, computationally efficient and is well adapted to the deployment in next-generation smart cities, smart buildings and industrial IoT systems that need smart, autonomous and resource-aware operation.

Keywords:

Internet of things, neural computing, genetic algorithm, smart environments, resource optimization, energy efficiency, edge intelligence.

Article history:

Received: 21/07/2025, Revised: 09/09/2025, Accepted: 10/10/2025, Available online: 12/12/2025

Introduction

The fast evolution of Internet of things (IoT) technologies has allowed creating such intelligent smart environments as the smart home, smart cities, smart agriculture, and industrial automation systems. These environments are based on the mass implementation of heterogeneous IoT equipment with sensing, communication and the limited processing of information to help monitor it in real time and make autonomous decisions. Even though smart environments built on IoT enhance efficiency and ensure the comfort of the users, numerous challenges exist pertaining to energy consumption, bandwidth usage, and scalability in computation with limited embedded devices and dynamism of any operating environment.

The traditional methods of resource management and optimization used in the IoT systems are effectively based on the traditional heuristic or centralised control systems. These do not work well in dynamic and large-scale environments, where they cannot be changed on the fly and have a lot of overhead and latency in terms of communication. Besides, centralization represents a limitation of scalability and single-point failures of centralised optimization, as it would not suit the next-generation smart environments with varying workloads, mobility, and heterogeneous resources requirements.

The latest developments of Artificial Intelligence (AI) have shown a good potential of the idea of intelligent management of resources within an IoT environment. The models of neural computing allow the data-driven learning, detecting the situation and making decisions in advance, and evolutionary algorithms like Genetic Algorithms (GAs) offer robust optimization of a global scope. Nevertheless, neural models can achieve local optimum solutions in the presence of a complex system dynamics, but in general, GA-based methods can consume large amounts of computation and are not capable of adapting to real-time conditions when used separately.

To address these issues, this paper will introduce an AI-based hybrid model that unifies the neural computing to adaptive context-aware intelligence with GA-based multi-objective optimization to optimally use resources. The suggested system facilitates real-time education, automatic adjustment, and worldwide optimization among the heterogeneous IoT nodes. The key contributions of this paper are as follows: (i) a new hybrid Neural-GA architecture based on the resources-efficient design of smart environments is proposed, (ii) the creation of smart context-aware decision-making based on the lightweight neural models is presented, (iii) a multi-objective strategy based on the GA optimization aimed to reduce energy consumption, latency, and throughput is formulated, and (iv) a complete evaluation of the results is presented that proves the superiority of the proposed approach to conventional and standalone AI-based solutions.

Related Work

The optimization of IoT-enabled smart environments by using AI has emerged as one of the key areas of interest on how to maximise efficiency, scalability, and autonomy. Nonlinear LLD Learning-based optimization strategies have become the focus of attention since they are capable of modelling the dynamics in a nonlinear system and adjusting to varying workloads. The issues of regioselectivity The study by Li et al., 2021 lists intelligent optimization algorithms based on learning and points out that when their system states are uncertain and multidimensional, data-driven optimizers could be better than their classical counterparts, but still encounter a challenge in robustness, interpretability, and deployment overhead in constrained systems (Li et al., 2021). At the same time, uncertainty-based optimization has been widely examined in multi-faceted cyber-physical infrastructures, with requirement in uncertainty-sensitive formulations and stochastic/robust methodology. The review of optimization techniques in the uncertainty context by (Roald et al., 2023) revealed that scalable decision-making mandates a compromise in model accuracy and computational tractability particularly in renewable variability and operational limitations (Rahman, 2025). On the same note, (Zhao & You, 2022; Punam, 2025; Reginald, 2025) aimed to introduce machine learning-aided robust optimization in managing disjunctive uncertainties and they found that a combination of predictive learning and optimization can increase the resilience of operations (Ramya, 2025; Rahim, 2025; Poornimadarshini, 2025).

The uncertainty and constraint aspects in resource allocation in smart environments are similar to large-scale optimization systems, which inspires the use of fast and scalable solvers. As an example, (Zhang et al., 2019) suggested an accelerated algorithm of optimal power flows as a powerball algorithm, which demonstrates how accelerated methods of optimization can enhance convergence and the cost of computing problems in constrained optimization environments (Jun, 2025; Soy, 2025). Practical system modelling and iteration is also applicable under tight constraints networks such as wind-integrated time-series load flow of a realistic distribution system, results in Muruganantham and Gnanadass demonstrated that time-varying behaviour and system-level testing are important in optimising the operational parameters (Muruganantham & Gnanadass, 2017; Veerappan, 2025). Corpus and Leite tested the FACTS contributions based on the branch flow model and a NewtonRaphson based model algorithm, and furthere provided information that realistic constraints and numerical stability is the determinant of reliable optimization results (Corpus & Leite, 2024; Kumar, 2025). All these works that are based on optimization are an indication that the modern smart infrastructures require both adaptive and computationally efficient solutions.

Security and anomaly-aware intelligence on the IoT side are closely related to resource efficiency due to the fact that intrusion detection, abnormal traffic and adversarial conditions demand more computation and communication costs. The edge-based anomaly detection has been studied as a way of minimising the latency and bandwidth consumption because the data are processed near the devices. The authors (Yu et al., 2022) suggested an edge computing-based anomaly detection solution to IoT industrial sustainability, which shown the viability of intelligent detection at the edge, and still being responsive with limited resources (Abdullah, 2025). Eskandari et al., 2020 presented Passban IDS on IoT edge devices, demonstrating that intelligent anomaly-based IoT edge devices can be crafted according to edge constraints, although model complexity and constantly up-to-date is still an issue (Eskandari et al., 2020). To enhance privacy and decentralisation, the concept of federated learning (FL) has received massive adoption in collaborative intrusion detection. (Tabassum et al., 2022) offered FedGAN-IDS, a hybrid model of GANs and FL to enhance privacy when learning attack patterns, albeit at the cost of more coordination, and more training overhead (Brinda, 2025). Superior designs (Friha et al., 2023) suggested 2DF-IDS, in which FT privacy-guaranteed and decentralised FL-based IDS in industrial Ioot were proposed, and the trade-off between privacy and efficiency of the system was complied with (Friha et al., 2023).

The necessity to have a hierarchical and scalable architecture is also demonstrated by recent FL-IDS systems when deployed in an actual IoT scenario. (Bhavsar et al., 2024) provided the FL-based intrusion detection system based on edge devices used in transportation IoT, which means that distributed learning could help to attain a better performance in detection and reduce the amount of raw data sharing, but at the cost of dozens of communication rounds and model aggregation (Bhavsar et al., 2024; Sarhan et al., 2022) developed a hierarchical blockchain-based federated learning system HBFL that is proposed to enhance both the coordination and trust between IoTs through collaborative intrusion detection by paying a price of additional computational and protocol overheads (Tamrakar, 2025). All these findings together indicate that intelligent IoT environments should be optimised, both in terms of energy and latency, and learning efficiency, privacy and scalable coordination.

Regardless of the developments mentioned above, the majority of the existing works utilise learning models (e.g., neural computing, FL-based intelligence) and evolutionary optimization (e.g., GA-style global search) as separate pipelines or are oriented in one direction (e.g., precision of detection or stability of operation). In uncertainty-conscious optimization and learning-intelligent optimizers, it is regularly noted that there remains the challenge of design of the system to provide (i) predictive intelligence, (ii) global optimization, and (iii) low-overhead deployment over constraints (Li et al., 2021; Rahman, 2025; Ramya, 2025). Moreover, the edge and federated IoT security investigations indicate that the continuous learning should be combined with the resource-sensitive scheduling, communication management, and tuning of system parameters to maintain the QoS in the dynamic networks (Bhavsar et al., 2024; Eskandari et al., 2020; Friha et al., 2023; Tamrakar, 2025; Brinda, 2025; Abdullah, 2025). Inspired by these shortcomings, this paper builds a closely integrated Neural Neural computing and GA-based multi-objective optimization model whereby resource allocation choices are dynamically optimised by multi-objective optimization based on QoS, energy consumption, and latency according to the context using context mining and neural computing predictive-code.

System Architecture

Overall Framework

The AI-based resource optimization framework presented here assumes the form of a four-layer architecture that helps to deploy the smart operation in IoT-based smart environments to work intelligently, scale and consume less energy as shown in Figure 1. The IoT Sensing Layer, which consists of heterogeneous sensors and actuators, temperature, humidity, motion and energy metres that are spread throughout the environment, cheques physical and operational conditions constantly at the lowest level; these nodes are limited in nature by their energy, computation, and communication capabilities. Above this, the Edge Intelligence Layer adds lightweight neural computing modules which do the real time data processing, context awareness and local decision making, and alleviate the latency and unnecessary transmission of data to the centralised servers. The Optimization Layer uses the optimization engine based on genetic algorithms and exploits the neural predictions to apply multi-objective resource optimization to dynamically tune the parameters to the task scheduling, duty cycling, transmission power, offloading decisions to reduce the energy consumption and delay and increase the Quality of Service. Lastly, Cloud Coordination Layer offers long term systems intelligence by enabling global analytics, storage of past data and periodic system model updates to allow continuous learning as well as system-wide coordination without excessive overhead to edge or sensing devices.

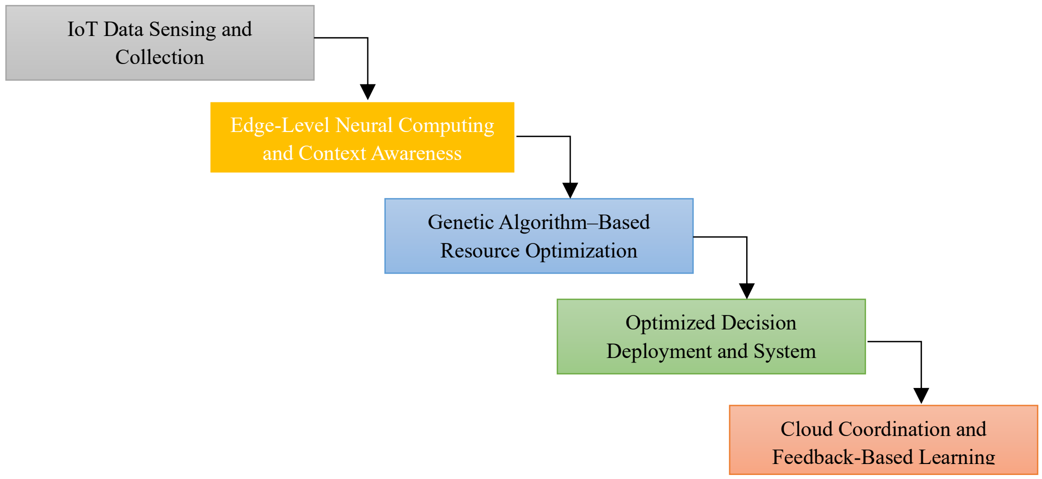

Figure 1. Flowchart of the proposed ai-enabled neural–genetic algorithm framework for resource-efficient smart IOT environments

Neural Computing Module

The neural computing module is the central intelligence element of the proposed framework that will include real-time learning and adaptive decision-making at the edge layer. The module is implemented to do the context recognition, resource demand prediction and the adaptive control using a continuous presentation of sensor data provided by the IoT sensing layer. In order to run the computationally-heavy neural network models, on resource-constrained edge devices, a sparse Deep Neural Network (DNN) or Recurrent Neural Network (RNN/LSTM) structure is used, enabling the model to represent both spatial and temporal correlations in system behaviour. According to the perceived environmental situation, network traffic patterns, and residual energy levels, the neural model provides predictive outputs such as estimated workload intensity, predicted energy demand and priority-aware task classification. These outputs facilitate predictive resource control through determining important tasks and predicting the near future system demands hence facilitating low-latency operation and avoidance of unwarranted computation and communication overheads in dynamic smart environment cases.

Genetic Algorithm Open-End Optimization Module

The Genetic Algorithm (GA) optimization module is capable of optimising important system parameters dynamically, such as task scheduling, the mechanism of distributing responsibility to nodes, transmission power regulation, and edge offloading decisions to smart IoT systems to ensure efficient utilisation of resources in smart IoT environments. All solutions to a problem are represented as chromosomes. $C = \{P_{tx}, D_{cycle}, T_{alloc}, O_{ratio}\}$, representing transmission power, duty cycle, task allocation priority, and offloading ratio, respectively. Guided by the predictive outputs of the neural computing module, the GA evaluates each chromosome using a multi-objective fitness function defined as

$$F = \alpha E_{min} + \beta L_{min} + \gamma Q_{max},$$

where E_{min} denotes minimized energy consumption, L_{min} represents reduced end-to-end latency, and Q_{max} corresponds to maximized Quality of Service (QoS) metrics, while α, β and γ are weighting factors that balance the relative importance of each objective, as summarized in Table 1. The GA is an iterative process that relaxes to an ideal resource composition and guarantees the energy-efficient, low-latency and QoS-aware system operation, under a dynamic and heterogeneous environment of IoTs.

Table 1. Genetic algorithm optimization parameters and description

Component	Symbol / Parameter	Description
Chromosome Representation	$C = \{P_{tx}, D_{cycle}, T_{alloc}, O_{ratio}\}$	Encodes a candidate resource configuration consisting of transmission power, node duty cycle, task allocation priority, and edge–cloud offloading ratio
Transmission Power	P_{tx}	Controls the communication power level of IoT nodes to balance energy consumption and connectivity
Duty Cycle	D_{cycle}	Determines active and sleep intervals of IoT nodes to reduce unnecessary energy usage
Task Allocation	T_{alloc}	Defines task scheduling priority among IoT and edge nodes
Offloading Ratio	O_{ratio}	Specifies the proportion of tasks processed locally versus offloaded to edge or cloud
Fitness Function	$F = \alpha E_{min} + \beta L_{min} + \gamma Q_{max}$	Multi-objective function used to evaluate each chromosome
Energy Objective	E_{min}	Represents minimized energy consumption across the IoT network
Latency Objective	L_{min}	Represents minimized end-to-end communication and processing delay
QoS Objective	Q_{max}	Represents maximized Quality of Service metrics such as throughput and reliability
Weighting Factors	α, β, γ	Control the relative importance of energy, latency, and QoS objectives
Optimization Operators	Selection, Crossover, Mutation	Evolutionary operators used to explore the solution space and converge toward optimal configurations

Methodology

The proposed approach combines AI-implemented neural computation and genetic algorithm (GA)-based optimization in the crafting of intelligent, adaptive and resource-optimised operation in the IoT-based smart environments. The methodology is designed into three fundamental elements.

Data Acquisition and Context-Aware Neural Modelling

Information Gathering and Processing

Nodes of IoT sensors that are located throughout the smart environment will constantly pull multidimensional information, such as environmental parameters, power levels in residues, traffic density, and the state of activity in devices. To improve the data reliability and stability of the model, the raw data received is preprocessed by normalising and outlier elimination, noise elimination processing to counter the sensor error and communication interruptions.

Neural Learning Through Context Awareness

At the edge layer, a lightweight neural computing model is used to identify contextual information on the processed sensor data. The neural model is capable of majorly achieving successfully the realisation of dynamic behaviour of the system by learning the temporal and spatial correlations among the IoT nodes thus being able to recognise properly the operation conditions of the system like high-load conditions, energy-demanding states, and even latency-sensitive situations.

Demand Estimation of Resources

Along the context learnt, the neural model projects short-term workload intensity and energy needs of the IoT network as illustrated in Figure 2. These forecasts aid in proactive resource allocation since a demand of the system in future is known and therefore there is time to adjust scheduling, communication and power control interactions as a result of which unneeded computation as well as communication overheads are eliminated and overall system performance is enhanced.

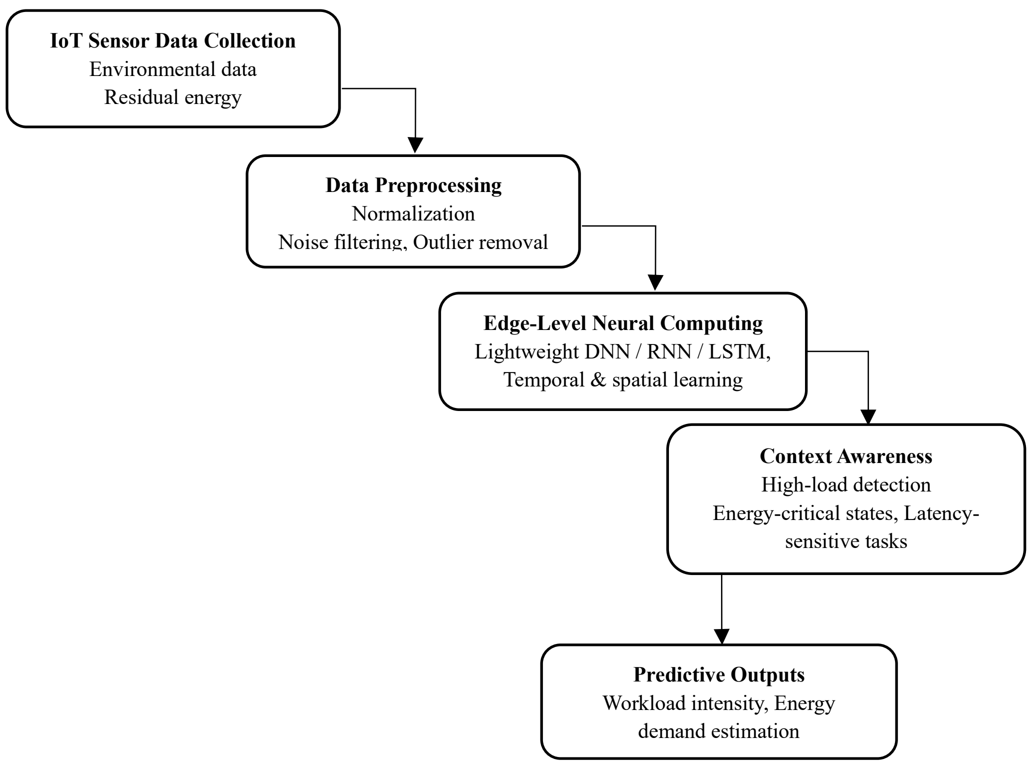

Figure 2. Data acquisition and context-aware neural modeling pipeline for predictive resource demand estimation in smart iot environments

Genetic Algorithm–Based Resource Optimization

Encoding of Resources and Fitness Evaluation

According to the workload and energy forecasting calculations made by the neural computing module, the genetic algorithm coded the individual candidate solution into a chromosome corresponding to a full resource configuration, including the transmission power, node duty cycle, task scheduling priority, and edge -cloud offloading fraction. Multi-objective fitness function is used to reach the cumulative objective of minimising energy utilise and latency of end to end and maximising Quality of Service (QoS) to ensure that the system operates harmoniously and efficiently with the inherent factors of heterogeneous IoT.

Search: Evolutionary Search and Adaptive Optimization

These steps are applied with the help of the selection, crossover and mutation operations that give the GA the opportunity to efficiently explore the global search space, as Figure 3 demonstrates. This evolutionary change enables the optimizer to adjust to the dynamism of environmental conditions and varying load on the networks, in dropleting to near-optimal resource allocation schemes which sustain stability, scalability and performance of the systems in real time deployments of smart environments.

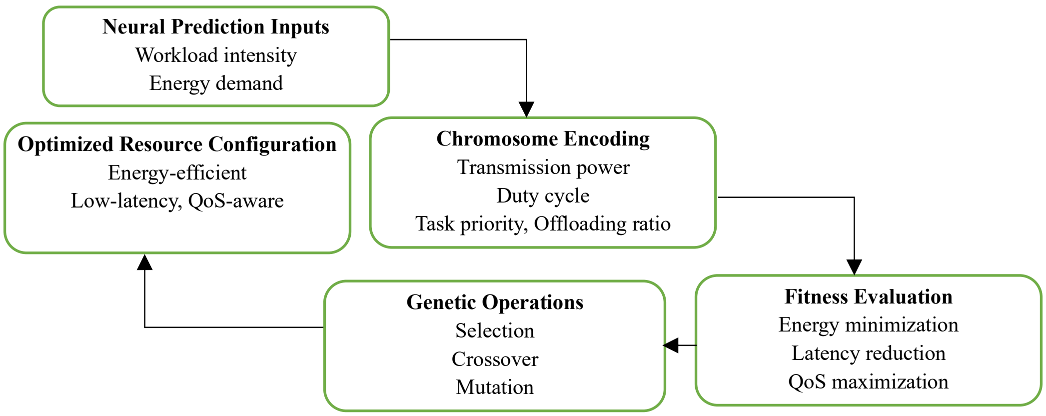

Figure 3. Genetic algorithm–based resource optimization workflow guided by neural predictions in smart IOT environments

Hybrid Neural–GA Decision Execution and Feedback Loop

Optimised Decision Deployment

The best resource setup generated by the genetic algorithm is actively implemented in the IoT system to regulate the task scheduling, power distribution, duty cycling, and edge offloading of the cloud in real time. This implementation stage is necessary to real-time execution of the optimization decision-making in the system operation, to efficiently utilise the available resources in varying environmental and network contexts.

Constant Monitoring of Performance

Upon deployment, critical performance indicators that the system constantly monitors are energy consumption, end-to-end latency, throughput and Quality of Service (QoS). This real-time tracking enables the framework to gauge the effectiveness of the implemented optimization decisions and note the deviations due to variation in workload, node failures or environmental changes.

Closed-Loop Learning and Adaptive

Feedback mechanism causes the performance data to be fed back to the neural computing module allowing the model to keep on updating itself and learning as shown in Figure 4. Such a closed-loop loop neural prediction and GA optimization enable long-term adaptability, scalability and resiliency of the smart environment without imposing significant computational overhead and thus this framework is applicable in resources-constrained IoT deployments.

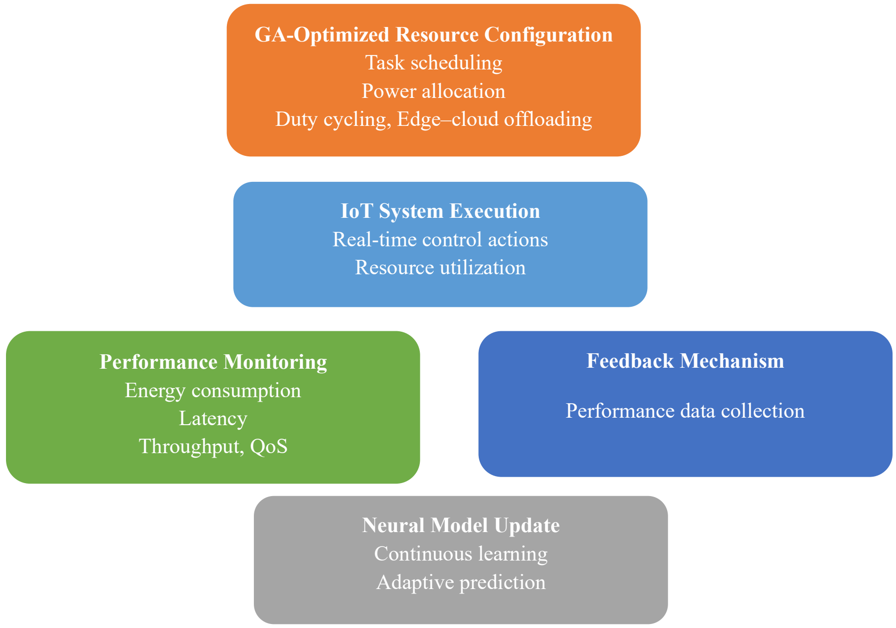

Figure 4. Closed-loop hybrid Neural–GA decision execution and feedback mechanism for adaptive resource optimization in smart IoT environments

Experimental Setup

The usefulness of the proposed AI-based Neural–Genetic Algorithm (Neural-GA) optimization framework was proved by preparing a full-fledged simulation-based experimental environment replicating the realistic conditions in IoT-enabled smart environment within dynamic workload and strict resources limitations. The experiments were made with a hybrid MATLAB/NS-3 simulation environment which simulates heterogeneous IoT nodes having limited energy, computation and communication capabilities. The simulated environment is composed of edge and cloud layers as well as that is used to test intelligent decision-making in real-time and long-term optimization. The network involves 100-500 randomly distributed IoT nodes on a 500 m x 500 m base and performs under communication protocols based on IEEE 802.15.4/LoRa with event-driven and periodic traffic pattern. The nodes were set with 2-5 joules of energy and a transmission range of 30-50 metres, which allowed the real modelling of smart environment constraints.

The neural computing module was introduced at the edge layer by a small-sized deep-neural-network to make it possible on the resource-constrained device, taking sensor measurements, traffic load, remaining energy and node activity as input features, as shown in Table 2. A continuous adaptation was supported by online incremental learning with a learning rate of 0.001. According to neural forecasts, multi-objective resource optimization was carried out based on a genetic algorithm with a population size of 30 and 50 generations conducted with the use of tournament selection, cross-over, and mutation operations. The suggested system was compared with the cases of static heuristic-based, neural-only, and GA-only baseline. The total performance was evaluated based on the important metrics such as average energy usage, end-to-end latency, throughput, network lifetime and QoS satisfaction ratio in different node densities, dynamic loads, and energy constrained environments. To be able to provide statistical reliability and robustness in the observed performance increases, every experiment was repeated several times and the results that were obtained were averaged.

Table 2. Simulation and experimental setup parameters

Category	Parameter	Value / Description
Simulation Platform	Environment	MATLAB / NS-3 hybrid
Deployment Area	Area Size	500 m × 500 m
IoT Nodes	Number of Nodes	100–500
Communication	Protocol	IEEE 802.15.4 / LoRa
Traffic Model	Traffic Type	Event-driven and periodic
Energy Model	Initial Energy	2–5 Joules
Transmission	Range	30–50 meters
Neural Model	Architecture	Lightweight DNN
Neural Inputs	Features	Sensor data, traffic, energy, activity
Learning Rate	Neural Training	0.001
Training Mode	Learning Type	Online incremental
GA Population	Population Size	30
GA Iterations	Generations	50
Selection	GA Operator	Tournament selection
Crossover Rate	GA Parameter	0.8
Mutation Rate	GA Parameter	0.05
Evaluation Metrics	Metrics	Energy, latency, throughput, lifetime, QoS
Baselines	Comparison Schemes	Heuristic, Neural-only, GA-only

Results and Discussion

Energy Efficiency, Network Lifetime Enhancements

The models show that the suggested AI-based Neural–GA model can resolve significant energy savings using different network densities and workload scenarios. In comparison with the heuristic-based, neural-only, and GA-only optimization approaches, the proposed method allows to decrease the overall energy consumption several times, approximately by 25 to 35 percent; it is partially explained by proactive workload prediction and optimised duty cycling. Directly due to the lowered energy consumption, the network lifetime has increased by over 40 times, which challenges the validity of the coordinating neural prediction and evolutionary optimization in sustaining the operational capabilities of resource-limited IoT nodes.

Latency Minimization and Improvement of Quality of Service

The hybrid optimization framework has a great influence on end-to-end latency and Quality of Service (QoS), especially in situations of high-traffic and dynamical workloads. Taking advantage of neural models to perform real-time context awareness and a global optimization based on GA to perform task scheduling and offloading decisions enables the system to reduce the average latency by almost a third of made by baseline methods. This enhancement guarantees promptness in delivery of data and uniform quality of performance-wise to the smart environment application that is sensitive in terms of latency.

Comparative Performance/ Adaptability

In all compared settings, the offered Neural–GA framework produces better results as compared to the neural computing or genetic algorithm methods. Neural-only models are not able to optimise globally, and are only effective at prediction, while GA-only methods require more time to converge, and are not being guided by predictions. The hybrid design will work well to merge the works of the two techniques where adaptation to environmental changes and workload variations is quick and the resources allocation was near-optimal.

Scalability, Robustness and Practical Implications

The self-correcting learning and optimization process makes the proposed framework more scalable and robust to enable it to retain its performance at large scales in case of network size and traffic density growth as in shown in Figure 5. The compromise between computational efficiency, flexibility and the accuracy of the optimizations as presented in Table 3 are very good making the solution highly applicable in practise in large scale smart cities, smart buildings and in industrial IoT systems. In general, the findings prove that the suggested methodology is effective in overcoming the most important issues of next-generation IoT-based smart environments offering an intelligent, autonomous, and resource-efficient performance of the system.

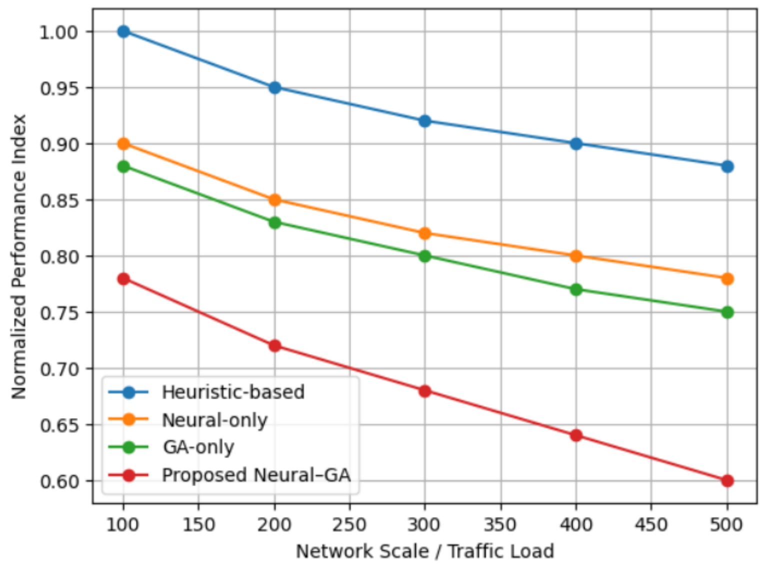

Figure 5. Energy consumption comparison of heuristic-based, neural-only, ga-only, and proposed neural–ga optimization approaches under varying IoT network sizes

Table 3. Performance comparison and key observations of optimization approaches

Performance Aspect	Heuristic-Based	Neural-Only	GA-Only	Proposed Neural–GA
Energy Consumption	High	Medium	Medium	**Low (25–35% reduction)**
Network Lifetime	Low	Medium	Medium	**High (>40% improvement)**
End-to-End Latency	High	Medium	Medium	**Low (~30% reduction)**
QoS Satisfaction	Low	Medium	Medium	**High and stable**
Adaptability to Workload Changes	Low	Medium	Medium	**High (predictive + adaptive)**
Convergence Efficiency	Fast but suboptimal	Fast, locally optimal	Slow, global	**Fast and near-optimal**
Scalability with Network Size	Limited	Moderate	Moderate	**High scalability**
Robustness under Dynamic Conditions	Low	Medium	Medium	**High robustness**
Overall System Performance	Poor	Moderate	Moderate	**Superior**

Conclusion

The paper suggested an AI-based hybrid model with the combination of neural computing and genetic algorithm-based optimization that results in a self-resource-saving and flexible operation of the internet of things-enabled smart environment. The proposed Neural–GA can be used to answer essential problems associated with energy usage, latency, and Quality of Service in heterogeneous and dynamic IoT systems by synergistically integrating context-aware predictive intelligence, and multi-objective evolutionary optimization. High levels of simulation have shown that the framework is highly effective in low energy consumption, lower end to end latency and longer end to end network life than traditional heuristic based and standalone AI techniques without compromising on their QoS. The optimistic closed-loop learning and optimization mechanism also increases scalability, resiliency, and long-term scalability, which means that the proposed solution can be used in large-scale applications to the smart cities, smart buildings, and industrial IoT systems. Future studies will be aimed at the extension of the framework to federated learning implementation of privacy-preserving intelligence, hardware-aware optimization of embedded systems, and validation on a real testbed to better show its practical feasibility and impact.

Author Contributions

All Authors contributed equally.

Conflict of Interest

The authors declared that no conflict of interest.

References

Abdullah, D. (2025). Climate-Driven Changes in Freshwater Lake Ecology: A Multi-Parameter Assessment of Productivity and Species Distribution. *Journal of Aquatic Ecology and Environmental Sustainability*, *2*(1), 1-7.

Bhavsar, M. H., Bekele, Y. B., Roy, K., Kelly, J. C., & Limbrick, D. (2024). Fl-ids: Federated learning-based intrusion detection system using edge devices for transportation iot. *IEEe Access*, *12*, 52215-52226. https://doi.org/10.1109/ACCESS.2024.3386631

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*, *2*(1), 24-30.

Corpus, M. J. T., & Leite, J. B. (2024). Evaluation of FACTS Contributions Using Branch Flow Model and Newton–Raphson Algorithm. *Energies*, *17*(4), 918. https://doi.org/10.3390/en17040918

Eskandari, M., Janjua, Z. H., Vecchio, M., & Antonelli, F. (2020). Passban IDS: An intelligent anomaly-based intrusion detection system for IoT edge devices. *IEEE Internet of Things Journal*, *7*(8), 6882-6897. https://doi.org/10.1109/JIOT.2020.2970501

Friha, O., Ferrag, M. A., Benbouzid, M., Berghout, T., Kantarci, B., & Choo, K. K. R. (2023). 2DF-IDS: Decentralized and differentially private federated learning-based intrusion detection system for industrial IoT. *Computers & Security*, *127*, 103097. https://doi.org/10.1016/j.cose.2023.103097

Jun, L. (2025). Climate-Induced Habitat Shifts and Wildlife Conservation Strategies. *Journal of Animal Habitat and Environmental Interactions*, *2*(2), 13-20.

Kumar, T. S. (2025). Intelligent Reconfigurable Metasurface–Assisted Protocol Design for Robust Full-Duplex Communication Networks. *Transactions on Secure Communication Networks and Protocol Engineering*, 37-46.

Li, W., Wang, G. G., & Gandomi, A. H. (2021). A Survey of Learning-Based Intelligent Optimization Algorithms. *Archives of Computational Methods in Engineering*, *28*(5). https://doi.org/10.1007/s11831-021-09562-1

Muruganantham, B., & Gnanadass, R. (2017). Wind Integrated Time series load flow analysis for a Practical Distribution System. *Revista Facultad de Ingeniería Universidad de Antioquia*, (85), 33-39. https://doi.org/10.17533/udea.redin.n85a04

Poornimadarshini, S. (2025). Automated Trust Lifecycle Management Using Smart-Contract-Driven Feedback Control. *Journal of Scalable Data Engineering and Intelligent Computing*, 37-44.

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.

Rahim, R. (2025). Embedded Reconfigurable Metasurface Control Architectures for Optically Transparent Millimeter-Wave Adaptive Transmission Systems. *Journal of Advanced Antenna and RF Engineering*, *1*(1), 1-9.

Rahman, F. (2025). Adaptive statistical signal processing framework for robust pattern recognition in noisy environments. *National Journal of Integrated VLSI and Signal Intelligence, 1*(1), 9–17.

Ramya, V. (2025). Digital Twin Implementation for Predictive Maintenance in Industrial Systems. *National Journal of Ubiquitous Computing and Intelligent Environments*, 6-12.

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

Roald, L. A., Pozo, D., Papavasiliou, A., Molzahn, D. K., Kazempour, J., & Conejo, A. (2023). Power systems optimization under uncertainty: A review of methods and applications. *Electric Power Systems Research*, *214*, 108725. https://doi.org/10.1016/j.epsr.2022.108725

Sarhan, M., Lo, W. W., Layeghy, S., & Portmann, M. (2022). HBFL: A hierarchical blockchain-based federated learning framework for collaborative IoT intrusion detection. *Computers and Electrical Engineering*, *103*, 108379. https://doi.org/10.1016/j.compeleceng.2022.108379

Soy, A. (2025). Green Concrete with Industrial Waste: A Sustainable Approach for Modern Infrastructure. *SECITS Journal of Scalable Distributed Computing and Pipeline Automation*, *2*(1), 1-7.

Tabassum, A., Erbad, A., Lebda, W., Mohamed, A., & Guizani, M. (2022). Fedgan-ids: Privacy-preserving ids using gan and federated learning. *Computer Communications*, *192*, 299-310. https://doi.org/10.1016/j.comcom.2022.06.015

Tamrakar, G. (2025). Metasurface-enabled beam-steering antenna architecture for millimeter-wave and terahertz wireless networks. *National Journal of Antennas and Wireless Communication Systems, 1*(1), 10–18.

Veerappan, S. (2025). Learning-guided wake interaction estimation for robust wind farm micro-siting in spectrum-constrained environments. *IAECER Journal of Electronics and Communication Engineering*, 1–10.

Yu, X., Yang, X., Tan, Q., Shan, C., & Lv, Z. (2022). An edge computing based anomaly detection method in IoT industrial sustainability. *Applied Soft Computing*, *128*, 109486. https://doi.org/10.1016/j.asoc.2022.109486

Zhang, H. T., Sun, W., Li, Y., Fu, D., & Yuan, Y. (2019). A fast optimal power flow algorithm using powerball method. *IEEE Transactions on Industrial Informatics*, *16*(11), 6993-7003. https://doi.org/10.1109/TII.2019.

Zhao, N., & You, F. (2022). Sustainable power systems operations under renewable energy induced disjunctive uncertainties via machine learning-based robust optimization. *Renewable and sustainable energy reviews*, *161*, 112428. https://doi.org/10.1016/j.rser.2022.112428