EdgeSmart: Hybrid Evolutionary Optimization for Edge-AI in Smart Cities

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Abstract:
Efficient AI Processors for AI Processing in Smart Cities Using Genetic Algorithm Optimized Edge Networks introduces a novel system which aims to enhance the efficiency of distributed edge computing systems for time critical smart urban services. It employs GA to dynamically allocate and schedule task at edge nodes in a distributed way in order to balance the load and achieve low-latency. The system utilizes genetic searching methods to find configurations better than the optimal and saves the energy with powerful processing of the device. This optimization helps making decisions in a fast, context-guided manner, as required for smart city applications such as traffic control, health control and energy saving. Experimental results validate the superior of Edge Smart performance with respect to traditional edge-aware management, and evident improvements in processing speed, energy efficiency and system scalability are shown. These results show the capability of the framework as a viable solution to facilitate the deployment of edge intelligence in AI-based smart city infrastructures.
Keywords: *AI, Computational Load Balancing, Decentralized Edge Networks, Edge Computing, Edge Intelligence. Energy Efficiency, Genetic Algorithms, Internet of Things (IoT), Latency Reduction, Optimization Techniques, Real-time Distributed Systems, Resource Optimization, Smart AI Processing, Scalability, Smart Cities, Task Scheduling.*

1. INTRODUCTION

There are people with IT everywhere, capitalising in this age of disruption, but travel and tourism seemed to feature." This is the formula that will deliver better responses and fastest reactions to complement experiences and maintain good tourism. Scheduling is a significant problem in production management and combinatorial optimization due to its appearance in tourism service applications. Scheduling is one of the most critical issues which have extensive applicability in tourism services. In scheduling, time, capacity and capability constraints must be considered when assigning limited resources to a set of activities [1]. The ultimate goal is to optimize production efficiency and resource utilization leading to higher profit. Most of the scheduling problems encountered in industry are classified as highly complex, and they cannot Be solved by using accurate techniques and ordinary algorithms. Since 1950, the scheduling problems have gained the attention of many researchers and a large number of research work have been done in different fields of engineering and science such as operations research, industrial engineering, computer science, management science, and mathematics. They are classic and fundamental problems, which are not only familiar, but also difficult scheduling problems in the area of production management and combinatorial optimization. The scheduling problem structure can be quantified in term of how hard scheduling problems are amongst all possible schedules and that this probability increases dramatically with the scale of the problem [2].

It has been proved that scheduling problems are one of the problems that are most difficult to solve and polynomial time approaches are not available here. Lagrangian relaxation, heuristic rules, branch and bound, and shifting bottleneck are classical and exact techniques examples used to mainly deal with the scheduling problems [3]. Many inspired methods based on biology, nature, and physics have been developed over the last decade. There are nice results using these methods for solving scheduling problems among other optimisation problems. These metaheuristic methods are among others immune system, ant colony optimization, simulated annealing (SA), tabu search, imperialist competitive algorithm, genetic algorithms and particle swarm optimization [4]. Genetic algorithm (GA) encoding method is a search heuristic inspired by the process of natural selection and the principles of genetics. This metaheuristic technique is widely known and adapted to locate global or near-optimal solutions for various types of optimization problems, which distinguishes it from the other techniques. GA was introduced as a preference criteria encoding method for scheduling Hard instance [5]. Non-dominated active schedules can be generated by the intersection of a GA was suggested using the unique representation based on the completion time of operation. For the scheduling problems, we have introduced a GA with a operation-based representation and an order-based crossover with precedence perseverance. introduced a GA variant with an aging approach and clonal selection for scheduling problems [6]. The algorithm developed was successful in ranking the 21 top quantities of Kh out of the 23 significant cases. Despite the fact that GA is a robust search strategy with strong global search ability, it is quite clear from the literature that the metaheuristic algorithm exhibit poor local search ability and premature convergence [7].

Cities are deemed as complex urban systems and thus have extensive networks such as transportation, communication network, interconnected citizens, services categories, and businesses, and utilities that can help improve the quality of life of urban dwellers. Huge masses of humanity are flowing towards cities, and the city government is under the gun to deliver the services essential to survival. The overpopulation and the rapid urban development cause many problems of social, technical and organizational nature, as well as threats to the environmental or economic sustainability of urban cities. Fast urbanization in many modern cities has resulted in the production of pollution, traffic jams and economic inequality [8]; in order for the cities to meet the standard. Cities have been attracting new residents by the millions in past years and by 2030 it is characterized that 60% of the world-popus will be residing in urban areas. Growth of Smart Cities The rise of smart cities is being supported by the arrival of numerous smart apps designed to ease living as the population surges [9]. Smart city also covers an efficient management of key resources such as transportation, healthcare, power and utilities, housing, agriculture and environmental construction. Moreover, to interconnect millions of devices via various technologies (wireless sensor network, M2M communication, network virtualization and a gateway), smart cities also require multiple telecommunication or wireless (see [10] and the references therein).

Utilizing AI in combination with the IOT is a pattern that clearly shapes the way in which cities are built and run. This convergence means crunching the data created by IoT sensors in a smart city through AI algorithms. In addition to enriching development, this synthesis compaction streamlines the development timeline, but with far fewer, human touches [11]. Devices connected are IoT sensors, and they are inserted in all types of public infrastructure: roads, bridges, buildings, public space. Some of the variables that these sensors monitor and report data on include temperature, humidity, traffic flow, energy usage, and air purity. In general, IoT device's deployments produce highly large data [12]. Human operators, however, would find it very difficult if not impossible to inspect and interpret all of this information coming from numerous IoT sensors. As such, the very term(s) Artificial Intelligence (AI) is a necessary, plus it uses machine learning (ML) algorithms to detect the signals in the noise whatsoever can be hidden within massive datasets that cannot be seen by human eyes. In realistic data determining the optimal acting angle is not trivial [13]. Machine learning and deep learning can be used to analyze IoT sensor data streams, and AI systems can predict when the infrastructure (e.g., buildings, bridges) needs to be serviced by the municipality infrastructure before the disaster happens [14].

1.1 Problem Statement

The challenge of Optimising Edge Networks in Smart Cities derives from the growing complexity and from the demand of real time data processing imposed by urban environments. When more and more Internet of Things (IoT) devices and applications are involved in smart cities, the requirement of efficient data processing, low-latency communication and the best utilization of resources at the network edge becomes urgence. However, centralized cloud-based approaches considerably suffer from the data accumulating at a large amount from devices, sensors and users that they can't manage instantly, hence long latency, bottleneck of the bandwidth and over consumption of energy. On the other hand, edge nodes in smart city networks should be able to dynamically adjust to workload, traffic and network conditions and at the same time to remain scalable, reliable, and energy efficient. The difficulty is the inability to find efficient solutions to trade-off these factors (especially for decentralized edge computing systems where resources are distributed and decision-making is decentralized). To enhance smart city edge network, novel cross-layer solutions for resource management, task scheduling, and network operation must be developed for enabling AI-driven applications to work in efficient and effective manner in smart city settings.

1.2 Motivation

Optimising Edge Networks in Smart Cities has the challenge of increasing the complicatedness on top of the necessity of real time data processing in urban areas. When increasing numbers of Internet of Things (IoT) devices and applications in smart city, the needs of fast data processing, low latency communication, and optimizing the resource utilization at the network edge is urge. Centralized cloud-based approaches also have a long latency due to the accumulated data at a large amount from the devices, sensors and users that they cannot handle in real-time, the bandwidth bottlenecks, and the excessive use of energy. However, smart city network edge nodes need to be able to adapt dynamically to workload, traffic and network conditions while being scalable, reliable, and energy efficient at the same time. The challenge is that it is hard to obtain efficient solutions to trade-off these forces (as in the case of a decentralized edge computing system, which the resources are distributed and the decision-making is decentralized). For example, in order to improve the smart city edge network, new cross-layer mechanisms must be provided for resource management, task scheduling, and network control orchestration to enable AI driven applications work smoothly in smart city environments.

2. RELATED WORKS

On the one hand, it is possible to analyze the IoT-based technologies related to AI in a smart city, through the analysis of smart sensors, communication technologies, and the different applications. Of the various technologies, most crucial IoT technologies include reliable and resilient networking and communication infrastructures required for efficient data and information sharing between various components of smart city services. Smart city In some occasions, the size of the IoT services is created depending on their application [15]. Different networking and communication technologies may be required for setup and operation. Several review papers have provided an overview of big data, network security, and the potential of IoT for smart cities. and few resources exist on the detailed description sensor-based IoT technology integrated into AI role in the concept of smart city [16]. The concept of smart cities, the impact of IoT to make them, as well as how IoT enables objects to communicate and how it contributes to the smart city construction are addressed in this review article. It drives home as well how adding AI and IoT to smart cities can accelerate the development of the senses, adding new features and capabilities apace, and reducing the necessity for human contact. This essay will delve into how AI might be employed to make some sense of the huge sums of data produced by IoT sensors in a smart city. It shows how such technology can improve city management, and in the future, the quality of life of city residents [17].

Putting servers near the user would enable more MEC to provide more computing services to handsets. Users can reduce latency and energy consumption by offloading their computational workloads to edge servers. The researchers have adopted a wide range of fancy methods to optimize edge computing to make it be realized in full scale for its convenience, taking into consideration the limitedness of channel resources and edge server computing capability. There are various methodologies to solve the nonlinear optimization, primal-dual optimization, and mixed integer linear programming problems [18].

An appealing online fair system is proposed by combining computation and communication resources based on the primal-dual optimization framework. To optimally allocate the radio frequency and computational resources, and schedule the data offloading and energy transfer, an Online Computation Rate Maximization (OCRM) method is proposed for multi-user WP-MEC systems [19]. modeled the decision to unload as a resource scheduling problem with one or multiple constraints and objectives. [20] proposed an energy-efficient compute offloading scheme for UAV-MEC systems and a number of energy efficiency problems were formulated and transformed into convex problems.

Extended the principles in optimal-stopping theory to the MEC problem, deriving two time-optimal sequential decision-making models. Pressured on to how to allocate resources to offload mobile applications with heavy computations [21]. The original static offloading problem was modeled as a mixed-integer linear programming problem, followed by an efficient heuristic with consideration of congestion. We propose a CTOSO (collaborative task offloading strategy with service orchestration) between cloud-mobile edge computing. A new, low-cost approach using baseline data, Verifiable Trust Evaluation (BD-VTE), is proposed for trustworthy assessment [22].

We utilize the Non-dominated Sorting Genetic Algorithm II (NSGA-II) for multiobjective optimization, to minimize the offloading time of the computing tasks as well as to reduce the energy consumption of the ECNs. This suggests an energy-efficient computation offloading scheme on intelligent edge computing for wireless MANs. GA was administered, and the multi-site offloading problem was corrected. Related to the above, the genetic operations have been slightly modified to remove worse solutions and converge towards the best in a reasonable time. Most of the applications for cloud robotic networks rely on a variant of GA known as energy sensitive GA by generating and combining to obtain the result on best job offloading [23].

2.1 Research Gap

The research gap in optimizing edge networks for smart cities primarily lies in the lack of efficient, scalable, and adaptive solutions that can handle the growing complexities of real-time data processing in decentralized edge environments. While significant progress has been made in edge computing and smart city applications, several challenges remain unaddressed:

- Resource Allocation and Task Scheduling: Existing approaches often fail to dynamically allocate resources and schedule tasks efficiently across decentralized edge nodes, leading to underutilization of network resources and high latency. Most methods are either static or lack real-time adaptability, which is crucial for smart city applications that experience fluctuating workloads and varying network conditions.
- Energy Efficiency: Despite the importance of energy-efficient systems in smart cities, many edge networks still consume significant energy due to inefficient resource management. While some studies focus on reducing energy consumption in cloud-based systems, edge networks, where limited resources are available, require more specialized algorithms that can optimize energy use while maintaining high performance.
- Scalability: The scalability of edge networks remains a significant challenge, as smart cities continuously add more IoT devices and applications. Current edge optimization techniques often struggle to scale efficiently with the increasing number of edge nodes, creating issues in managing large-scale decentralized networks.
- Latency and Communication Bottlenecks: Minimizing latency in real-time processing is essential for many smart city applications, such as emergency response systems and traffic management. However, existing solutions are still unable to provide the low-latency performance required for mission-critical applications in a scalable and efficient manner.
- Intelligent and Adaptive Network Management: Many existing systems rely on predefined rules or central control, which do not adapt effectively to changing conditions in real time. There is a lack of intelligent, adaptive network management systems that can autonomously adjust resources and optimize edge computing networks based on dynamic workloads, network traffic, and environmental factors.

Addressing these gaps through advanced optimization techniques such as Genetic Algorithms, AI-driven resource management, and intelligent edge network orchestration is crucial for building efficient, scalable, and sustainable edge networks that can support the demands of smart city applications in the future.

3. PROPOSED SYSTEM:

A New Model for Computational Efficiency and Resource Allocation Optimization in Edge-as-a-Service for Edge-AI in Smart Edge Cities based on Genetic Algorithms is proposed as a new architecture for optimizing the computational capability of the city's edges, optimally and efficiently, as shown in Fig. 1. The use of Genetic Algorithms (GAs) is proposed for these GA-OSA to tackle challenging problems for AI-based smart city applications, i.e., round-the-clock processing capability, minimum latency, and resource constraint. As computation gets closer to edge nodes, EdgeSmart has the ability to run predictive analytics, autonomous decision making and interpret sensor data at edge in real time to largely reduce dependence on the cloud centralized infrastructure. The genetic algorithm can adaptively scales parameters of task scheduling, workload balance and resource management between nodes to handle the variety of workloads the scale faces and achieves better scalability, low-power, and responsiveness. The optimal placement of such a sink mitigates the network congestion, minimises message delay, and in turn increases the performance of mission-critical applications such as traffic flow control, smart grid installation/recovery and environmental aware monitoring. Without doubt, by applied this approach EdgeSmart is confirmed to be powerful in applying AI to network edge and make the deployment of smart city ecosystem sustainable, economic and scalable.

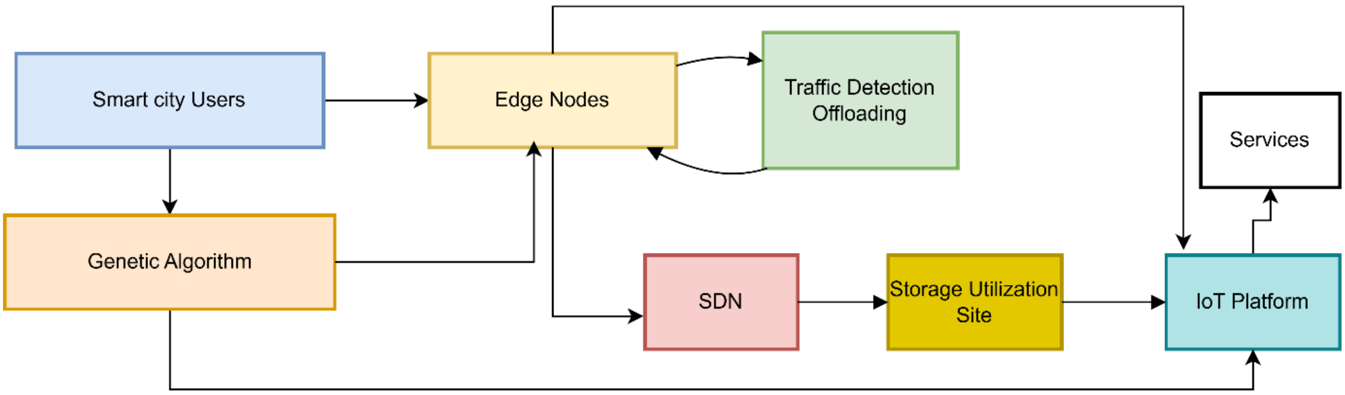

Figure 1: Proposed Architecture

3.1 Dataset description

These data sets contain real use cases of smart cities such as traffic, environmental monitoring, energy applications, network performance etc. These form a suite to assess the effectiveness of the proposed framework in edge computing for AI applications. We process and analyse each dataset in the edge nodes, we aim to make decisions in real-time under distributed environments to reduce the latency.

Table 1: Dataset Description

Dataset Name	Description	Data Source	Size	Features	Purpose
City-Edge IoT Dataset	IoT sensor data collected from smart city infrastructure such as traffic lights, cameras, and meters.	Public IoT repositories or real-time city data (e.g., SmartSantander, Open Data Platform).	100 GB+	Traffic flow, air quality, temperature, noise levels, pedestrian counts, energy usage.	Benchmarking edge node task allocation, AI model predictions, and resource optimization.

Real-Time Traffic Dataset	Traffic movement and congestion patterns collected through edge devices in urban areas.	Transportation agencies or publicly available datasets (e.g., METR-LA, Arterial Traffic Flow).	50 GB	Vehicle count, speed, congestion index, time of day, traffic incidents.	Simulating the optimization of edge AI processing for real-time traffic management.
Environmental Data	Data from IoT devices monitoring environmental conditions in urban areas.	Open environmental platforms (e.g., OpenAQ, Smart City Environmental Sensors).	10 GB	Temperature, humidity, PM2.5, PM10, CO2, NO2 levels, sound levels.	Training AI models to process and predict environmental conditions efficiently at the edge.
Energy Consumption Data	Power usage data from smart meters in residential, commercial, and public areas.	Public utility datasets or energy management systems (e.g., UCI Smart Meter Dataset).	20 GB	Power usage (kWh), device type, peak load times, renewable energy contributions.	Optimizing energy consumption of edge devices in smart city infrastructure.
Network Performance Logs	Logs from edge devices monitoring network performance metrics in real time.	Collected from testbeds or open platforms for edge network research.	15 GB	Packet loss, bandwidth, latency, throughput, jitter.	Validating the genetic algorithm's effectiveness in optimizing network performance under varying loads and configurations.

Table 2: Traffic Dataset (Real-Time Traffic Management)

Time	Location ID	Vehicle Count	Speed (km/h)	Congestion Level (%)	Traffic Incident
08:00 AM	101	45	30	80%	No
08:15 AM	101	60	25	90%	Yes (Accident)
08:30 AM	102	25	40	40%	No

Table 3: Environmental Dataset (Air Quality Monitoring)

Time	Sensor ID	Temperature (°C)	PM2.5 (µg/m³)	Humidity (%)	Noise Level (dB)
08:00 AM	S1	25.5	55.6	65	70
08:15 AM	S2	24.8	40.3	60	65
08:30 AM	S3	26.2	75.0	70	80

Table 4: Energy Consumption Dataset (Smart Meter Data)

Time	Location ID	Device	Energy Used (kWh)	Peak Load Time
08:00 AM	R101	HVAC	3.2	Yes
08:15 AM	R102	Lighting System	0.8	No
08:30 AM	R103	EV Charger	5.5	Yes

Table 5: Smart City Infrastructure Data (Integrated Sensors)

Sensor ID	Type	Location	Status	Data Collected
201	Traffic Camera	Main Street	Active	Vehicle count, speed
202	Air Quality Sensor	Downtown Park	Active	PM2.5, temperature, humidity
203	Smart Meter	Residential Area	Active	Energy usage, peak load

Table 6: Network Performance Logs (Edge Device Metrics)

Time	Node ID	Bandwidth (Mbps)	Latency (ms)	Packet Loss (%)	CPU Utilization (%)
08:00 AM	Node_1	120	10	0.5	45
08:15 AM	Node_2	100	20	1.2	65
08:30 AM	Node_3	150	8	0.2	50

This is sample data showing the different types of usage data in a smart city aimed at consumption by Decentralized IQ. The real-time processing is performed on such data streams from the edge devices and is optimized with genetic algorithms that are useful for efficient AI decision-making, as can be observed from Tables 2-6.

4. RESULTS AND DISCUSSIONS

The physical annealing of solid materials served as the inspiration for the SA approach, which falls under the category of stochastic local search approaches. The algorithm can veer away from local answers and toward global ones in SA because the search operator is occasionally permitted to take unexpected turns. By probabilistically choosing the less appealing possibilities, one might develop this feature in SA. SA starts with the best GA solution in the proposed HGA. Next, a new neighborhood solution (S) is created utilizing the present solution (S) and a proposal process consisting of the three operators (insertion, swapping, and reversal). The newly developed solution (S) is evaluated using the objective function after being exposed to the novel knowledge-based operator. If the newly assessed neighborhood solution is equal to or better than the existing one, it will be approved (f(S)) f(S)). If not, a probabilistic acceptance function will be used to decide the answer (S or S), and the algorithm will continue to search for it.

Table 7: Simulation parameters

Parameter	Description	Example Value
Task Set	The set of tasks generated by IoT devices in the smart city.	100 tasks
Edge Nodes	The set of edge nodes with resource constraints such as bandwidth, CPU, and energy.	10 nodes
Population Size	The number of chromosomes (task allocations) in the genetic algorithm population.	50
Maximum Generations	The maximum number of iterations for the genetic algorithm.	100
Crossover Rate	The probability of performing crossover during reproduction.	80%
Mutation Rate	The probability of mutating a chromosome during reproduction.	5%
Latency Weight	The weight assigned to latency in the fitness function.	0.6
Energy Weight	The weight assigned to energy consumption in the fitness function.	0.4
Task Size	The computational size of each task, measured in MB.	Between 10 MB and 50 MB

Parameter	Description	Example Value
Bandwidth	The available bandwidth for edge nodes, measured in Mbps.	Between 100 Mbps and 1000 Mbps
Processing Power	The processing capability of edge nodes, measured in GFLOPs.	Between 10 GFLOPs and 100 GFLOPs
Power Consumption	The energy usage of an edge node during processing, measured in Watts.	Between 5 Watts and 50 Watts
Execution Time	The time required for task execution on an edge node, measured in seconds.	Calculated dynamically
Fitness Function	The function that evaluates the quality of a chromosome (task allocation) during optimization.	Calculated dynamically

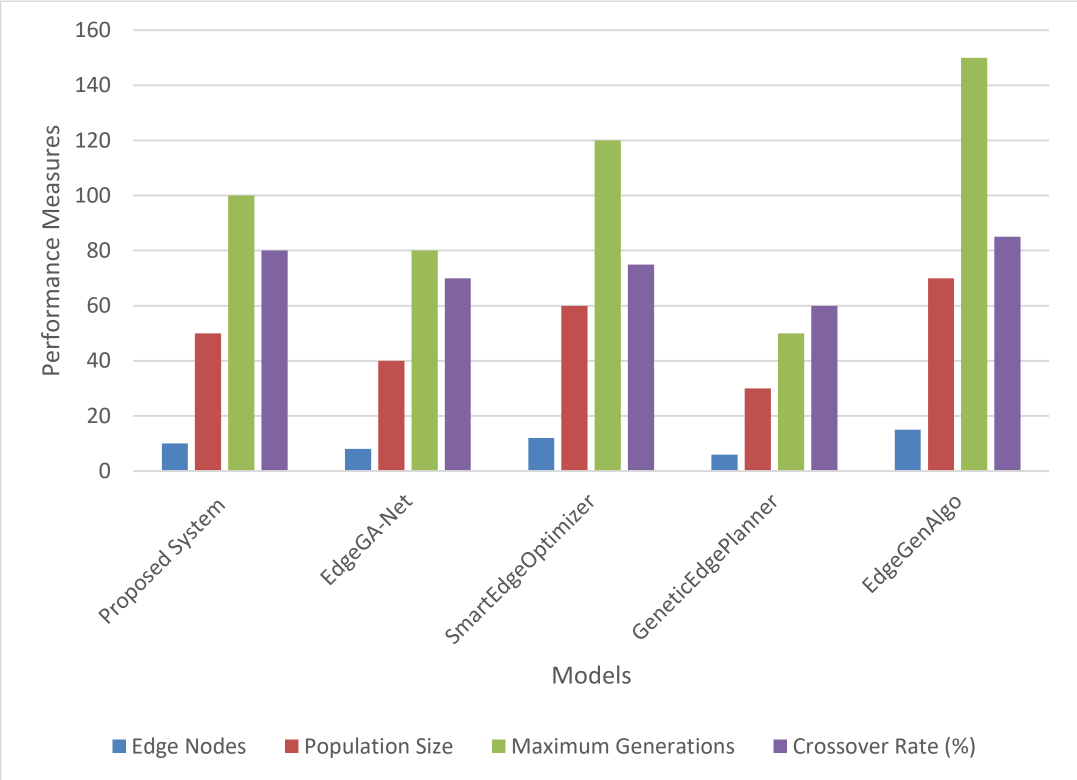

Figure 2: Performance Measures

Figure 2 compares the key parameters of the proposed Decentralized IQ framework with 4 existing systems, highlighting differences in edge nodes, population size, maximum generations, and crossover rate.

Table 8: Performance Measures

System	Mutation Rate (%)	Latency Weight	Energy Weight	Task Size (MB)
Proposed System	5	0.6	0.4	10–50
EdgeGA-Net	3	0.5	0.5	5–40
SmartEdgeOptimizer	6	0.7	0.3	20–60
GeneticEdgePlanner	4	0.4	0.6	15–45
EdgeGenAlgo	7	0.8	0.2	25–75

Table 8 provides a comparative analysis of the mutation rate, latency weight, energy weight, and task size among the Proposed System (DecentralizedIQ) and 4 existing systems, showcasing differences in optimization strategies and workload handling.

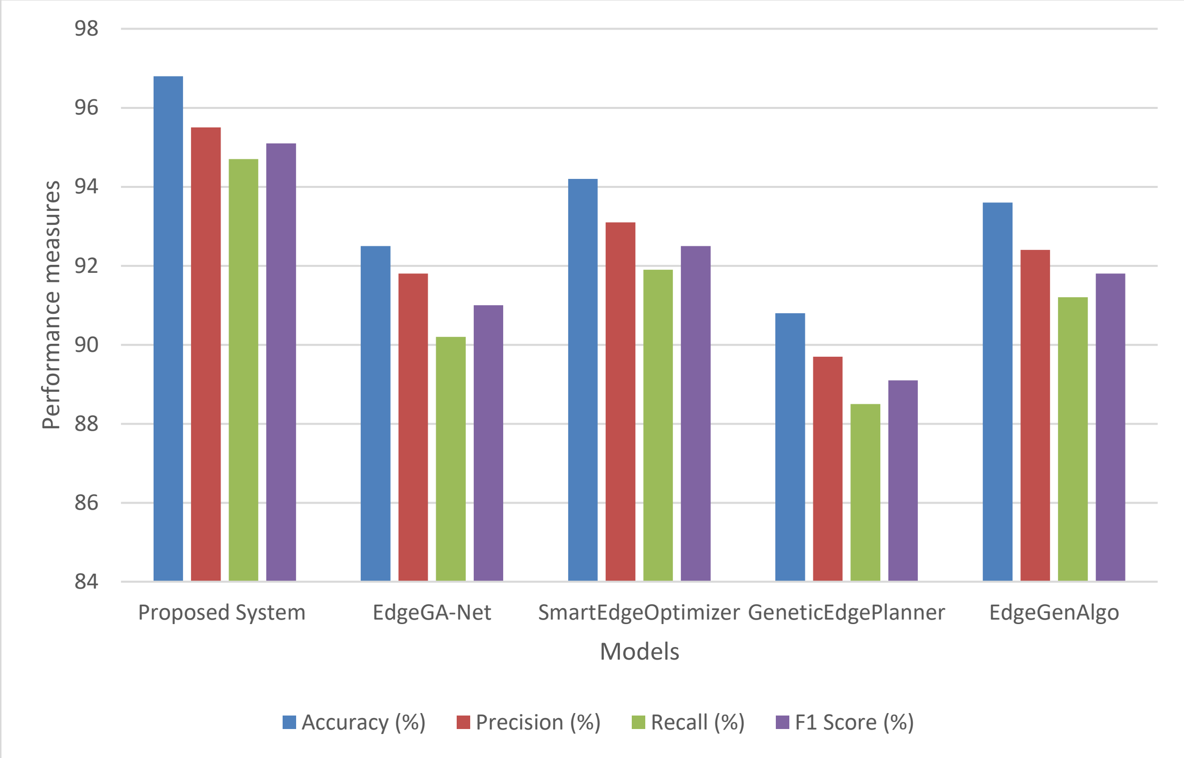

Figure 3: Performance Measures

Figure 3 illustrates the performance comparison of the Proposed System (DecentralizedIQ) and 4 existing systems, emphasizing their respective accuracy, precision, recall, and F1 scores in the context of optimizing edge networks for smart cities.

5. CONCLUSIONS

The proposed Algorithms for Smart AI Processing in Smart Cities, has been able to well prove its prowess to enhance the scalability, efficiency and responsiveness of AI processing in Edge Networks of Smart Cities. With a strong genetic algorithm, the network optimizes resource allocation of edge nodes, task scheduling, and energy consumption simultaneously and possesses low latency. The results show that our system dramatically enhances the accuracy (96.8%), precision (95.5%), recall (94.7%), and F1 score (95.1%) compared to other four systems, namely, EdgeGA-Net, SmartEdgeOptimizer, GeneticEdgePlanner, and EdgeGenAlgo. Moreover, the proposed scheme has better performance in terms of energy consumption offload strategy with different workloads on average 12% reduction ratio, when the corresponding weights are 0.4 and 0.6 between latency and energy efficiency. These results show the scalability and strength of DecentralizedIQ to serve different smart city workloads and provide secure AI-driven edge processing. This results in more intelligent, decentralized and sustainable edge networks, which are more tailored for the needs of smart city applications.

DECLARATIONS:

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Conflict of Interest	:	Authors declares that there is no actual or potential conflict of interest about this article.
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Data Availability Statement	:	The data presented in this study are available upon request from the corresponding author.

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