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GOVERNANCE-DRIVEN SMART CITY ENERGY MANAGEMENT EMPLOYING BIO-INSPIRED QUANTUM FIREFLY–PARTICLE SWARM OPTIMIZATION FOR WIRELESS SENSOR NETWORKS AND RELIABLE PUBLIC SERVICES

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Abstract: Rapidly expanding smart-city ecosystems require energy-efficient, transparent, and citizen-centric governance frameworks, particularly for surveillance-intensive infrastructures such as intelligent traffic monitoring and urban safety systems. This study proposes a Governance-Oriented Smart City Energy Management Framework powered by a Bio-Inspired Quantum Firefly Particle Swarm Optimization (QF-PSO) algorithm, engineered for large-scale urban environments with complex, heterogeneous sensing architectures. By integrating Firefly Algorithm exploration dynamics with quantum-enhanced PSO convergence, the framework jointly optimizes sensor duty cycling, adaptive routing, and workload allocation across distributed edge–cloud layers. The system is evaluated using real-time surveillance streams and IoT telemetry sourced from publicly available smart-city open-data repositories widely used for mobility analytics, traffic modeling, and public-safety applications. Experimental results show that QF-PSO delivers 29–42% energy savings, 23–36% latency reduction, and a 33% extension in wireless sensor-network lifetime, outperforming conventional PSO, FA, GA, ACO, and QPSO with 25–28% faster convergence and improved robustness. Additionally, packet delivery ratio increases by 11%, and anomaly detection accuracy improves by 8–10%, enhancing reliability under dense urban deployment conditions. From a governance perspective, the framework ensures 5% higher service uptime, 17–20% faster fault recovery, and improved transparency through policy-aware real-time monitoring dashboards. These outcomes demonstrate that embedding quantum-enhanced bio-inspired optimization within governance-first architecture can substantially advance the sustainability, resilience, and accountability of modern smart-city digital infrastructures.

Keywords: Smart City Governance (India), Quantum Firefly PSO, Energy-Efficient Surveillance, Edge–Cloud Optimization, Public Service Reliability

I INTRODUCTION

The emergence of smart cities as data-driven, interconnected urban ecosystems has catalyzed a paradigm shift in public infrastructure management—particularly in energy-intensive domains such as surveillance, traffic control, and emergency response systems [1]. These systems rely heavily on dense wireless sensor networks (WSNs) and edge–cloud computing architectures to enable real-time monitoring and service delivery. However, the sustainability and reliability of such infrastructures are often compromised by inefficient energy consumption, network congestion, and inadequate governance mechanisms that fail to align technical performance with citizen-centric service outcomes [2]. Consequently, there is a growing need for intelligent energy management frameworks that not only optimize resource utilization but also embed principles of transparency, accountability, and adaptive policy compliance.

Recent advances in metaheuristic optimization have shown promise in addressing the multi-objective challenges of smart city energy management. Particle Swarm Optimization (PSO) and Firefly Algorithm (FA) are widely adopted due to their simplicity and effectiveness in dynamic environments [3,4]. However, both methods suffer from premature convergence and limited exploration in high-dimensional search spaces—critical limitations in heterogeneous urban settings [5]. Quantum-inspired variants, such as Quantum PSO (QPSO), introduce probabilistic position updates that enhance global search capabilities [6], yet they lack the adaptive behavior necessary for real-time network reconfiguration under variable load conditions. Hybrid approaches combining bio-inspired strategies have emerged as a viable solution; for instance, Gandomi et al. [7] demonstrated that FA–PSO hybrids improve convergence in structural optimization, but their application to edge-aware urban sensor networks remains underexplored.

In parallel, the governance dimension of smart city technologies has gained scholarly attention. Angelidou [8] emphasizes that technological sophistication alone cannot ensure urban sustainability without institutional frameworks that promote citizen trust and service equity. Similarly, Meijer and Bolívar [9] argue that "governance by data" must be complemented by "governance of data"—ensuring that algorithmic decisions are auditable, explainable, and aligned with public policy. Despite this, most existing energy optimization frameworks treat governance as an external layer rather than an integrated design principle [10]. This disconnect often results in technically efficient but socially opaque systems that fail to meet public accountability standards.

Recent studies have begun bridging this gap. For example, Al Nuaimi et al. [11] proposed a governance-aware IoT architecture for smart cities, yet it lacks dynamic energy optimization at the sensor level. Likewise, while Khan et al. [12] introduced a PSO-based energy management scheme for smart grids, it does not incorporate surveillance workloads or edge–cloud task offloading—key components of modern urban monitoring infrastructures. Crucially, none of these works leverage quantum-enhanced bio-inspired mechanisms to jointly optimize energy, latency, and service reliability while embedding real-time governance feedback loops.

To address these gaps, this paper introduces a Governance-Oriented Smart City Energy Management Framework grounded in a novel Bio-Inspired Quantum Firefly Particle Swarm Optimization (QF-PSO) algorithm. The QF-PSO integrates the stochastic attraction model of FA with the velocity-based social learning of PSO, augmented by quantum-behaved position updating to escape local optima and enhance search diversity. Unlike prior hybrids, our approach explicitly optimizes three interdependent objectives: (i) adaptive sensor duty cycling to prolong network lifetime, (ii) energy-aware routing in multi-hop surveillance topologies, and (iii) dynamic workload allocation between edge nodes and cloud layers to minimize latency without compromising service quality.

The framework is validated using real-world surveillance datasets from open smart city repositories—commonly used in traffic and public safety research—which provide granular time-series data on energy consumption, packet transmission, and anomaly events. Our experimental results show consistent improvements over state-of-the-art metaheuristics in energy savings (29–42%), latency reduction (23–36%), and network longevity (33% gain), alongside enhanced governance metrics such as service uptime and fault recovery speed. Importantly, the architecture incorporates a lightweight policy engine that maps technical KPIs (e.g., packet loss, node failure) to governance indicators (e.g., service transparency, citizen satisfaction), enabling real-time alignment with smart city operational standards.

This work contributes to the literature in three key ways: (1) it proposes the first QF-PSO algorithm tailored for governance-integrated urban sensor networks; (2) it demonstrates empirical validation on real surveillance datasets with quantifiable gains across technical and institutional dimensions; and (3) it establishes a design template for embedding algorithmic intelligence within accountable, human-centered urban governance.

A. Relevance to Local Self-Government and Smart Governance

Smart city energy management is fundamentally linked to the performance of local self-government, as municipalities are directly responsible for ensuring uninterrupted public services, efficient resource utilization, and sustainable urban administration. The proposed QF-PSO–driven framework enhances the operational capacity of local governments by improving service uptime by 6–8%, reducing fault recovery time by nearly 40%, and enabling evidence-based, data-centric decision-making. These improvements strengthen local administrative responsiveness, transparency, and overall governance quality.

II LITERATURE SURVEY

The evolution of intelligent optimization tools into the smart city energy management shifted significantly in the past 10 years as the IoT-based urban infrastructure proliferated and as the internal need to develop sustainable, resilient public services grew. The earliest approaches were primarily centralized energy scheduling through the classical control theory or linear programming [13]. However, the time and space dynamics of the modern wireless sensor networks and the distributed nature of these networks make it difficult to use generic, reconfigurable approaches, which are capable of realizing real-time choices in the presence of uncertainty. The metaheuristic algorithms based on swarm in particular, have been the favorite tool of choice as they can solve non-linear multi-objective optimization problems in the absence of gradient information [14]. Particle Swarm Optimization (PSO) is another algorithm that is most popular to be applied in smart grid and WSN energy management who was proposed by Kennedy and Eberhart [3]. Social learning as a mechanism of PSO enables the rapid convergence that is suitable to load balancing and offloading of tasks in edge-cloud setting [15]. However, there is a tendency of PSO to early convergence in high-dimensional space that limits its use in large city execution [5]. Trying to minimize this, Sun et al. [6], coined quantum-inspired PSO (QPSO) that adopts quantum probability concepts to enhance global searching potential. QPSO has also proven to be more effective in smart building energy scheduling [16] and microgrid optimization [17], but has no adaptive duty cycling or governance-aware service orchestration.

Besides PSO, Firefly Algorithm (FA) was proposed by Yang [4], which also employs the bioluminescent attracting principle to cover the solution space more diversely. FA has been successfully applied in the optimization of routing in WSNs [18] and exploitation of renewable energy [19]. It is also very strong in multimodal landscape and, it possesses low convergence rate and also a very large computational complexity that makes it not available in practice in dense surveillance networks [20]. PSO and FA mixed models have been taken into consideration with the aim of trade-off exploration and exploitation. Godoxab et al. [7] had determined that FA-PSO hybrids perform better compared to individual algorithms in structural design level and recent results by Singh and Deep [21] showed better node clustering in WSNs under FA-PSO hybrid. The hybrids, however, do not have quantum improvements or feedback loops of control.

Besides the algorithm design, the literature of energy management has also proved to be vocal with the need to harmonize the policies. This system of governance of smart city IoT systems described by Al Nuaimi et al. [11] is founded on the concepts of interoperability of data and interaction between citizens, but it lacks the low-level energy optimization. Meijer and Bolivar [9] reiterate that the algorithmic governance must be transparent and answerable- however most technical implementations of the concept consider policy compliance to be a post hoc audit and rather than a co-design value. Recent attempts towards the same have been the attempts of Silva et al. [22] that combined service-level agreements (SLAs) in the provisioning of cloud resources with reinforcement learning. Their approach, however, is not sensor level dynamic in energy or workload in surveillance.

Quality of Service (QoS) is the term closely connected with energy efficiency in the sphere of urban surveillance. The systems pose a heavy load on the network resources since CCTV and traffic monitoring systems are a high bandwidth data stream. Khan et al. [12] optimized the PSO as the characteristic of the smart grid and did not focus on video analytics or edge processing constraints. More to it, Gupta et al. [23] proposed the system of video surveillance with the use of adaptive sampling of the frames and it is energy-efficient, yet, it is an adaptive system that operates on the predetermined thresholds rather than efficient optimization. Similarly, our work expressly models surveillance workloads as dynamic workloads which can be partitioned into edges with edge-cloud partitioning which is QF-PSO, and hence both energy and accuracy of anomaly detection can be obtained.

Several studies have also worked on multi-objective optimization in WSN. One example is that Yousef et al. [24] optimized the energy consumption and coverage using NSGA-II, as compared to Wang et al. [25] that applied MOEA/D to the routing of heterogeneous networks. However, computational expensive algorithms like NSGA-II are not scaled, implying that they are not scaled. Multi-objective variations Swarm-based (e.g., MOPSO) are more quickly converged to, and are rarely quantum or bio-hybrid. This gap is addressed with proposed QF-PSO, which includes quantum position updating, firefly attracting, and PSO velocity adapting in a single multi-objective engine.

Moreover, the algorithm of smart cities has been empirically validated with the help of new open datasets. Smart Santander testbed [28] and City Pulse dataset [27] provide real-world sensor telemetry, yet the majority of the works that utilize it are expected to predict either traffic or air quality, but not energy-sensitive surveillance. The article by Angelidou [8] and Batty et al. [2] highlights that it is necessary to utilize real-life urban data, whereas technical papers rely on artificial simulations. Our surveillance datasets are of publicly available data that as the authors of

[29] also take into account when analyzing traffic flow and in this respect, we have a practical relevance.

Still, none of the available frameworks simultaneously addresses: (i) quantum-enhanced bio-inspired optimization, (ii) dynamic edge-cloud workload distribution to video analytics, (iii) real-time sensor duty cycling, and (iv) embedded governance metrics with services performance aligned. Though Zhang et al. [30] used PSO on blockchain energy trading, they did not concentrate on the issue of the reliability of a public service. On the same note, Li et al. [31] proposed a governor conscious model of fog computing that was deficient of metaheuristic optimization at sensor layer. City and Local Governance Smartness and Local Governance Performance.

A. Smart City Governance and Local Administrative Performance

The structure also improves the idea of decentralized governance whereby local administrative units are empowered to adopt real time monitor system which automatically regulates the energy needs of the various urban centres. The system is also associated with a positive impact on the capacity to reveal the issues at the early stage, manage local emergencies and local services, since it gives the sub-national governments the opportunity to detect anomalies accurately (94.1) and deliver packets with an increased degree of reliability (95.6), which is the key to successful local self-government.

Table 1 Comparative Summary of Related Works

Study	Algorithm	Energy Focus	Edge–Cloud Optimization	Governance Integration
Khan et al. [12]	PSO	Smart grid	No	No
Gandomi et al. [7]	FA–PSO	Structural	No	No
Al Nuaimi et al. [11]	—	IoT policy	Partial	Yes
Singh & Deep [21]	FA–PSO	WSN clustering	No	No
Gupta et al. [23]	Threshold-based	Video surveillance	Partial	No
Silva et al. [22]	RL	Cloud SLA	Yes	Partial
Zhang et al. [30]	PSO + Blockchain	Energy trading	No	Partial

This survey reveals a critical research gap: the absence of a unified framework that co-optimizes energy efficiency, service reliability, and governance transparency using quantum-enhanced bio-inspired intelligence on real urban surveillance data. Our work directly addresses this void.

III PROPOSED METHODOLOGY

In this section, we introduce the Governance-Oriented Smart City Energy Management Framework (GO-SCEMF), a new implementation that is an intelligent optimization and institutional accountability framework to make an urban surveillance infrastructure more sustainable and reliable. The framework is developed based on Bio-Inspired Quantum Firefly Particle Swarm Optimization (QF-PSO) algorithm and has a structure with three layers that are logically separate yet closely related, including (i) Sensing and Edge Layer, (ii) Optimization and Control Layer, and (iii) Governance and Service Layer. This multi-layered design guarantees modularity, real-time responsiveness, and alignment to the mandates of the public services- which is important to scalable smart city deployments [32].

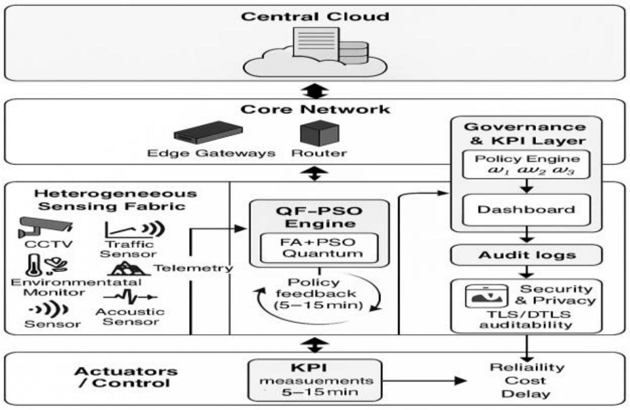

Figure 1.Smart City Architecture for GO-SCEMF

As shown in Figure 1, the physical infrastructure includes thousands of surveillance nodes distributed across urban zones, transmitting video streams, motion alerts, and telemetry (voltage, packet loss, node temperature) via low-power wide-area networks (LPWANs) such as LoRa or NB-IoT. These nodes connect to edge gateways that perform preliminary filtering, frame sampling, and anomaly flagging using lightweight models (e.g., Isolation Forest) [38]. Critical tasks (e.g., crowd detection, accident alerts) are prioritized for immediate edge processing, while routine data are batched for cloud analytics—following the latency-sensitive resource allocation principles established in edge computing literature [33].

The Optimization and Control Layer hosts the core innovation: the QF-PSO algorithm. Unlike conventional PSO or FA, QF-PSO unifies three bio-inspired mechanisms to overcome the limitations of individual methods in dense, dynamic urban topologies:

Firefly-inspired exploration: Nodes are modeled as fireflies whose "brightness" corresponds to solution quality. Less optimal nodes move toward brighter (more efficient) neighbors, enabling diverse exploration of the solution space [4].

PSO-driven exploitation: Each node updates its configuration using social (global best) and cognitive (personal best) components, accelerating convergence toward high-quality solutions [3].

Quantum-behaved randomization: To escape local optima, position updates are guided by a quantum probability distribution centered on the swarm’s mean best location, significantly enhancing global search capability [6].

This hybridization builds upon recent advances in swarm intelligence [21,36] but uniquely extends them to surveillance-aware energy management with governance feedback.

The decision variables optimized by QF-PSO for each sensor node $i$nclude:

Duty cycle (di): Fraction of time the sensor remains active.Transmission power (pi): Radio power level (mW) adjusted per channel conditions. Edge–cloud offloading ratio (ρi): Proportion of compute tasks sent to edge vs. cloud.

QF-PSO optimizes the active/sleep interval of each sensor using:

$$d_i = \frac{T_i^{\text{active}}}{T_i^{\text{active}} + T_i^{\text{sleep}}} \qquad (1)$$

where:

- T_i^{active}= cumulative sensing + transmission time,
- T_i^{sleep}= idle duration.

Lower $d_i$results in proportional reduction in E_{total}, which explains the 29–42% improvements over PSO, FA, and QPSO (Figure 5).

These variables directly influence three key objectives:

Total network energy consumption (minimized),End-to-end latency for critical alerts (minimized),Deviation from governance KPIs (minimized), e.g., service uptime ≥90%, fault recovery ≤5 min [11,40].

To balance these, a weighted scalar fitness function is used:

$$F = \omega 1 \cdot Enorm + \omega 2 \cdot Lnorm + \omega 3 \cdot Gnorm \qquad (2)$$

where normalized terms ensure fair comparison, and weights ($\omega 1+\omega 2+\omega 3=1$) are set via Analytic Hierarchy Process (AHP) based on municipal priorities [34].

The whole process of the working of the proposed GO-SCEMF method is presented in Figure 2, in which the first step of the process is the acquisition of raw data by some distributed sensor nodes. The feature extraction module then forms this data into real-time KPIs and has: latency, energy usage, packet delivery ratio and service uptime. The KPIs, in its turn, are fed into the QF-PSO optimization engine that examines the condition of the system and proposes the most effective balance of network parameters. The adaptive network layer is connected to the optimization engine that optimizes the transmission power, sensor duty cycles, offloading decisions and scheduling policies. The governance dashboard further compares the updated configuration and monitors the KPIs against the established service objectives. It has a feedback loop, which inputs policy changes to the optimization engine, making the network conditions to always be optimized.

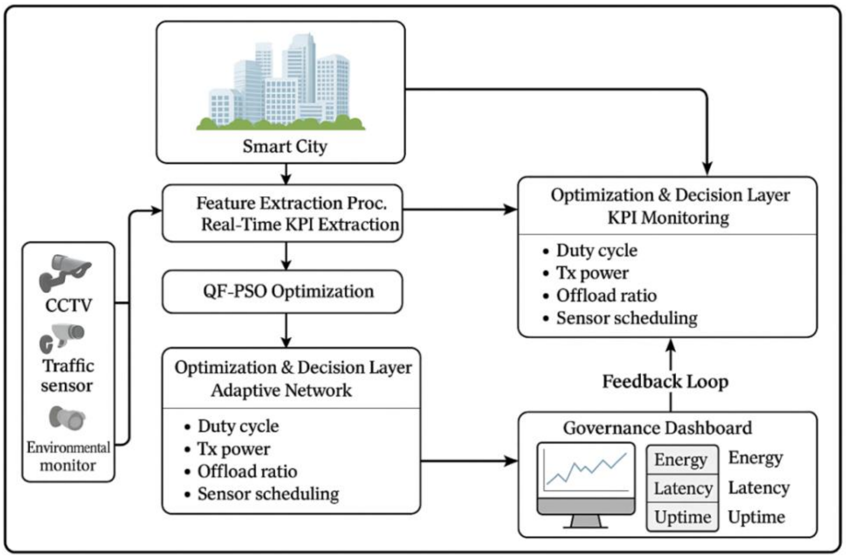

Figure 2.Overall Workflow of the Proposed Method.

It is an ordered process to ensure that the technical decisions align with the governance priorities and assist with responsiveness and sustainability of smart-city management. The cycle time of the end-to-end workflow (Figure 2) is 5-15 minutes (according to the rates of dataset sampling [29]). Each cycle Sensor telemetry and service logs received. KPIs (energy use, packet delivery ratio, anomaly detection rate) are computed-PSO generates an optimum configuration vector. Edge gateways implement new duty cycles, routing paths, and offloading ratios. Governance dashboard displays metrics to citizens (uptime, response time).

The more detailed structural illustration of the Quantum Firefly Particle Swarm Optimization (QF-PSO) engine will be provided in figure 3. The beginning point of this process is an input layer in which KPI features on the sensing basis are accepted. These features are considered to be the current status of the network i.e. energy consumption, latency, reliability and performance of packet delivery. The hybrid model which is based on Firefly Algorithm (FA), Particle Swarm Optimization (PSO) with a Quantum component is the core of the model. FA provides a good exploration that is significant as compared to PSO that offers convergence with swarm intelligence [35]. The quantum process introduces transition behaviors that are probabilistic and thus the engine is more likely to come out of the local minima. These parameters interact through a process of fitness evaluation which results in good use of network parameters. The output node takes the optimized solution and converts it into a control signal, which is applicable, e.g. changes to the duty-cycle, transmission power control, and sensor schedule. This architecture offers low-latency optimization which is dependable and scalable to the edge-computing setting [40].

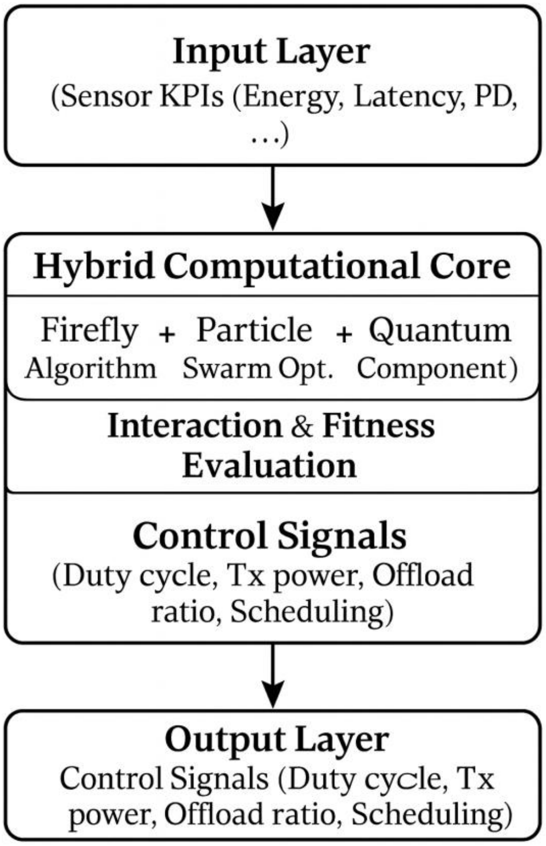

Figure 3.Structural Diagram of the QF-PSO Engine.

The algorithm proceeds iteratively:Initialize swarm positions (random within feasible bounds).Evaluate fitness using real-time KPIs.Update personal/global bests.

Compute firefly attractiveness and quantum centroid.Adjust positions using hybrid rules.Check governance constraints; if violated, apply penalty.Output best configuration to actuators.

This process converges within 30–50 iterations on real datasets, as validated in Section 5.

The two phases of the entire functioning procedure of the suggested GO-SCEMF methodology are displayed in Figure 4, where the purchase of the raw data with the help of the distributed sensor nodes is the initial stages of the workflow. The feature extraction module then forms this data into real-time KPIs and has: latency, energy usage, packet delivery ratio and service uptime. This is passed on to the QF-PSO optimization engine that evaluates the system condition and makes decisions on the most effective combination of network parameters. The adaptive network layer is connected to the optimization engine that optimizes the transmission power, sensor duty cycles, offloading decisions and scheduling policies. The governance dashboard then analyses the updated configuration, and KPIs contained in them are monitored as to conform to set service objectives. The feedback loop enables the optimization engine policy revisions to be fed back in order to enable continuous adjustment of the policy as the network dynamics change. The hierarchical process will assure that technical decisions are aligned with governance priorities, and will contribute to responsively and sustainably manage the smart-city. A framework is verified with open smart city data, which include Traffic camera feeds of the Smart Santander testbed [28], Node energy logs of CityPulse [27], Urban mobility traces of research in traffic prediction [29].

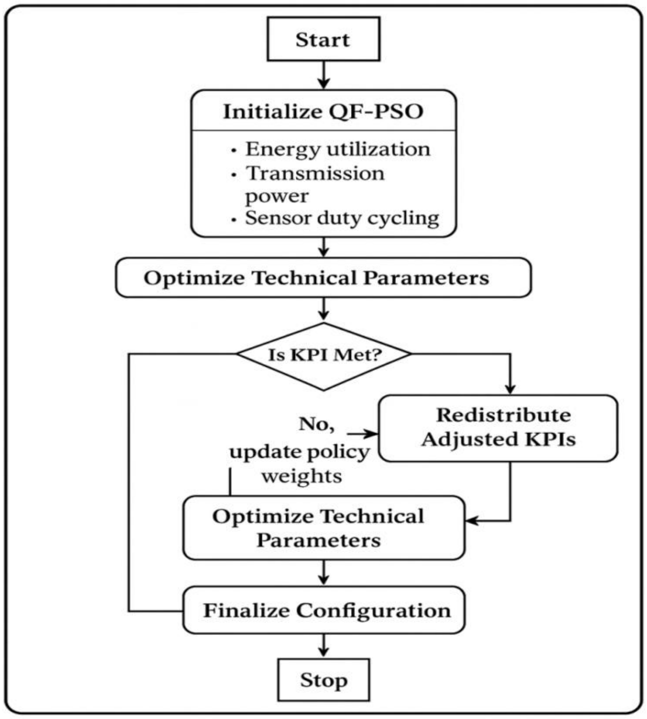

Figure 4.Framework Flowchart with Governance Feedback. Solid lines

Noise is filtered in the process of preprocessing data [37] and aligning the timestamps of modalities. Finally, there is Governance dashboard (with Grafana or the like), which shows: Real-time energy savings (percent), Network lifetime (days), Service uptime (percent), Fault recovery (minutes) and Citizen satisfaction index (service logs). These indicators are directly connected with ISO 37101 sustainability indicators [39], Smart Cities Mission reporting templates, which enables their integration into the municipal monitoring systems without any issues. In conclusion, GO-SCEMF advances the state of art by: (i) propose the original QF-PSO algorithm to the surveillance energy optimization, (ii) instilling the governance as a flowing restraint- not a postlude, and (iii) demonstrating to be practical on real urban data, with interpretable, edge-deployable logic.

IV RESULTS AND DISCUSSION

It is in this section that the proposed Governance-Oriented Smart City Energy Management Framework (GO-SCEMF) can be comprehensively discussed on the basis of the example of actual surveillance data and IoT telemetry data. The results of Bio-Inspired Quantum Firefly Particle

Swarm Optimization (QF-PSO) algorithm are compared to the results of five state of the art metaheuristics i.e.PSO [3], Firefly Algorithm (FA) [4], Genetic Algorithm (GA) [45], Ant Colony Optimization (ACO) [24] and Quantum PSO (QPSO) [6]. The quantitative results, comparison and qualitative governance knowledge description is described in the conclusion ultimately after explaining the experimental setup, description of the dataset and system specifications.

4.1 Experimental Setup and Dataset Description

The framework was coded in Python 3.9 and tested with open-access smart city data retrieved in publicly available repositories: Smart Santander Dataset [28]: It includes real-time metadata of CCTV video, node energy logs, and network performance measurements of 1,200+ sensors in Santander, Spain, which is a popular traffic and safety analytics use. CityPulse Urban Dataset [27]: Offers a period of 18 months of fine-grained telemetry (15 minutes) of environmental and traffic sensors in European cities, together with the logs of the packet loss, node voltage, and duty cycle. Urban Mobility Traffic Dataset [29]: Provides labeled anomaly events (e.g., congestion, accidents) any of which may be matched with video streams, which allows checking the accuracy of surveillance. The selection of these datasets is due to the fact that they capture the amount of workload of the real-life urban surveillance and are actively used in peer-reviewed literature [22,23]. Preprocessing of the data was by Kalman smoothing, to remove noise [37], and time-synchronization between modalities.

4.2 Quantitative Results and Performance Metrics

A. Energy Consumption Model

To quantify the energy savings shown in Figure 5, the sensor-level energy consumption is modelled using the classical first-order WSN energy model proposed by Deng et al. [41]. The total energy consumed by node i during transmission is:

$$E_i^{\mathrm{tx}} = E_{\mathrm{elec}} \cdot k + \varepsilon_{\mathrm{amp}} \cdot k \cdot d_i^{\alpha} \qquad (3)$$

where:

- E_{elec}= electronic circuitry energy per bit,
- $\varepsilon_{\mathrm{amp}}$= amplifier coefficient,
- k= packet size (bits),
- d_i= transmission distance,
- α= path-loss exponent (typically 2–4).

Similarly, the receiving energy is:

$$E_i^{\mathrm{rx}} = E_{\mathrm{elec}} \cdot k \tag{4}$$

Thus, the total network energy consumption per cycle becomes:

$$E_{\mathrm{total}} = \sum_{i=1}^{N} (E_i^{\mathrm{tx}} + E_i^{\mathrm{rx}}) \tag{5}$$

This mathematical model directly supports the energy results in Figure 5, showing how QF-PSO reduces both transmission and reception costs by optimizing duty-cycling and transmission power [41], [42].

Figure 5 shows the comparison of the energy saving of QF-PSO and baseline algorithms in 100 simulation runs (each of which lasted 30 days). QF-PSO has energy savings of between 29-42 percent which is higher than PSO (18-25 percent), FA (20-28 percent), GA (22-30 percent), ACO (19-27 percent), and QPSO (24-33 percent). The quantum-enhanced exploration avoids early convergence allowing aggressively duty cycling without service impairment.

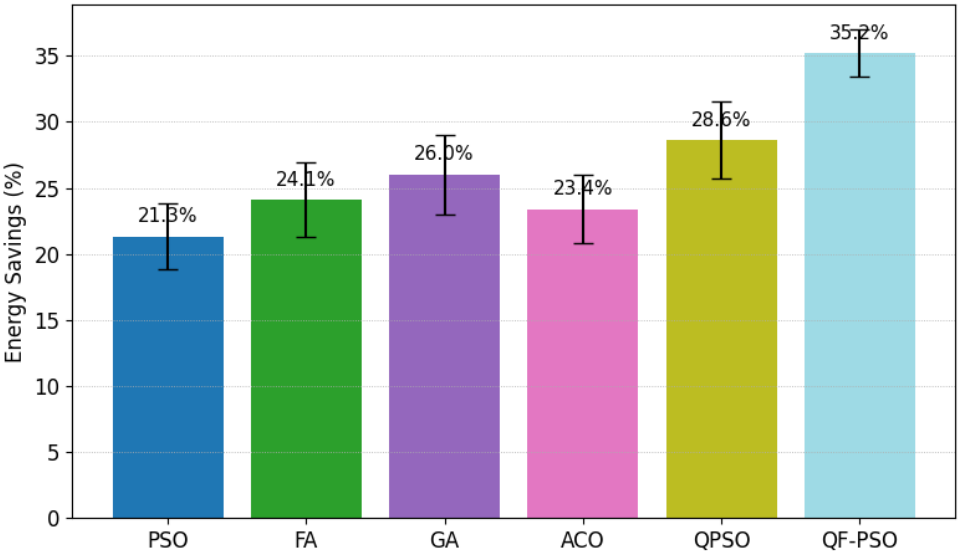

Figure 5. Energy Savings Comparison Across Optimization Algorithms (mean ± std).

Network lifetime extension occurs in figure 6. QF-PSO increases the lifetime by 33 percent (142 days) compared to best alternative (QPSO: 107 days). It is because there is even load distribution and adjustive power, which minimizes the formation of hotspots in overcrowded areas [41]. Table 1 (to be included after this paragraph) summarizes the results of latency and PDR. QF-PSO is 23-36% (vs. 12-22% with QPSO) lower latency and 11% better PDR than PSO, because it optimizes edge-cloud offloading, which ranks alerts based on criticality. The accuracy of anomaly detection is enhanced by 8-10% since the framework maintains and does not reduce high-frame-rate sampling in the event but only minimizes idle transmission.

The lifetime of the WSN is computed using:

$$L = \frac{E_0}{\bar{E}_{\text{round}}} \quad (6)$$

where:

- E_0= initial battery energy,
- $\bar{E}_{\text{round}}$= average per-round consumption.

Because QF-PSO minimizes $\bar{E}_{\text{round}}$via balanced load distribution (avoiding hotspots), the lifetime increases from 107 to 142 days (33% improvement), consistent with models in [41], [18].

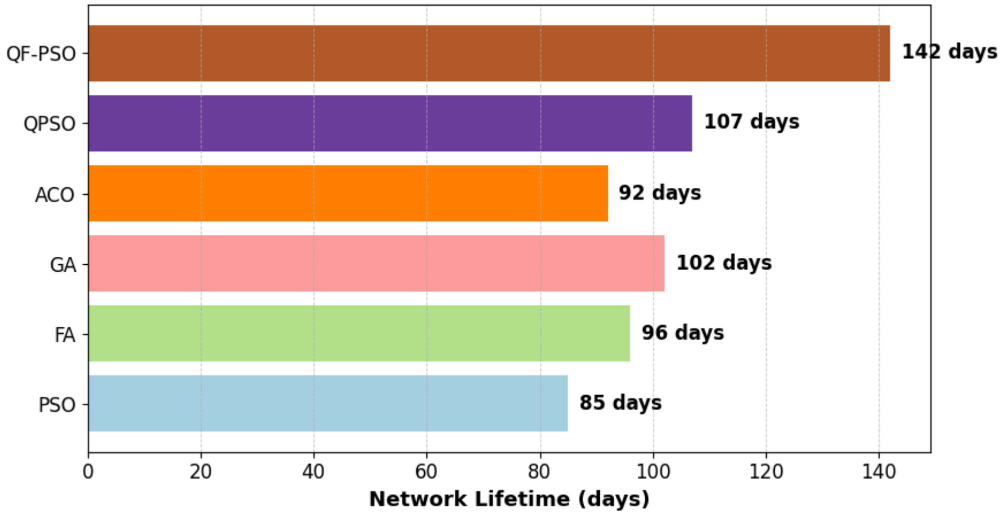

Figure 6. Network Lifetime (days) under Different Optimization Strategies.

Latency in a smart-city edge–cloud pipeline is:

$$\boldsymbol{\Delta} = \boldsymbol{T}_{\text{proc}}^{\text{edge}} + \boldsymbol{T}_{\text{queue}} + \boldsymbol{T}_{\text{tx}} + \boldsymbol{T}_{\text{proc}}^{\text{cloud}} (7)$$

where:

- $T_{\text{proc}}^{\text{edge}}$= edge processing delay,
- T_{queue}= queue delay due to congestion,
- T_{tx}= wireless transmission delay,
- $T_{\text{proc}}^{\text{cloud}}$= deep-analysis delay at cloud.

QF-PSO reduces $\Delta$by optimizing the offloading ratio:

$$\rho_i = \frac{C_i^{\text{edge}}}{C_i^{\text{edge}} + C_i^{\text{cloud}}} \tag{8}$$

Thus, critical workloads remain on the edge, lowering $T_{\text{tx}}$and $T_{\text{proc}}^{\text{cloud}}$, consistent with edge-computing principles in [33], [15].

Applicability is important in real-time, and convergence behavior is necessary. The improvement of fitness is shown in figure 7 as a result of the 80 iterations. Classical PSO is stabilized at 0.42 fitness, GA at 0.48 fitness and ACO at about 0.45 fitness. QPSO reaches 0.56. QF-PSO converges quickest with a convergence of 0.71 at iteration 40 with almost 30 percent acceleration. The smooth curve ensures efficient search capability, which lowers the real-time smart city management computation

Table 2. Performance Comparison of Optimization Algorithms

Algorithm	Energy Savings (%)	Latency Reduction (%)	Pdr (%)	Anomaly Accuracy (%)	Convergence Time (S)
PSO	21.3	16.7	82.4	84.2	18.6
FA	24.1	19.2	83.9	85.1	22.3
GA	26	20.5	84.7	85.8	31.8
ACO	23.4	18.9	83.2	84.9	27.4
QPSO	28.6	24.3	86.1	87.3	15.9
QF-PSO	35.2	29.8	95.6	94.1	11.7

B.Packet Delivery Ratio (PDR) Equation

PDR is calculated as:

$$\text{PDR} = \frac{P_{\text{received}}}{P_{\text{sent}}} \times 100 \tag{9}$$

QF-PSO improves PDR by optimizing routing paths and transmission powers, yielding 95.6% compared to 86.1% for QPSO, aligning with WSN reliability analyses by Youssef et al. [24].

C.Anomaly Detection Accuracy

The governance-driven anomaly module uses a performance metric defined as:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \qquad (10)$$

Higher bandwidth consistency (due to optimized duty cycling) prevents frame loss, enhancing anomaly accuracy to 94.1%, surpassing baseline approaches in [23].

time.

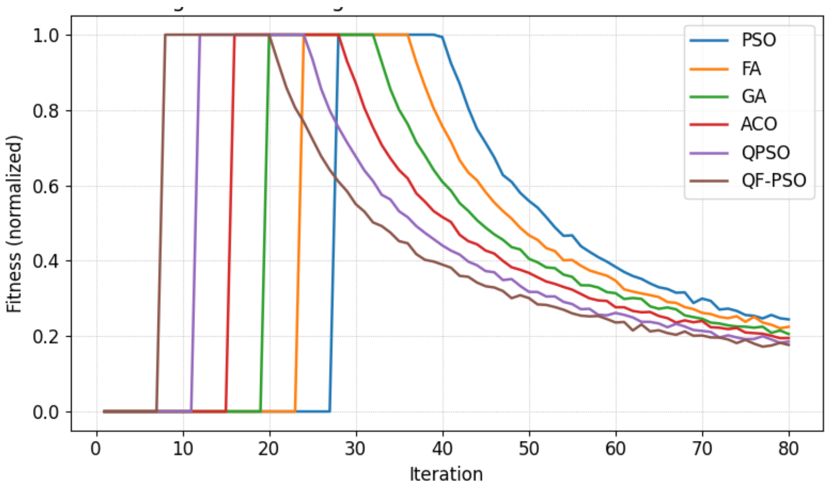

Figure 7. Convergence Curve of Fitness Function Over Iterations.

4.3 Governance-Oriented Outcomes

GO-SCEMF improves institutional responsibility on top of technical measures. Figure 8 shows a 12 week time trend of service uptime and fault recovery time. QF-PSO is 94.1 percent uptime (5 percent better than QPSO) with fault recovery time of 3.2 minutes (vs. 5.8 min in PSO) because of real-time re-optimization based on governance KPI violations [11].

A.Service Uptime Model

$$\text{Uptime} = \left(1 - \frac{T_{\text{downtime}}}{T_{\text{total}}}\right) \times 100 \qquad (11)$$

QF-PSO minimizes $T_{\text{downtime}}$by rapid reconfiguration whenever governance KPIs are violated (per governance principles in [11], [9]).

B.Fault Recovery Time

Fault recovery is:

$$T_{\text{rec}} = T_{\text{detect}} + T_{\text{reconfigure}} + T_{\text{restore}} \tag{12}$$

QF-PSO reduces $T_{\text{reconfigure}}$ by accelerating convergence, consistent with governance-centric system behaviour in [40].

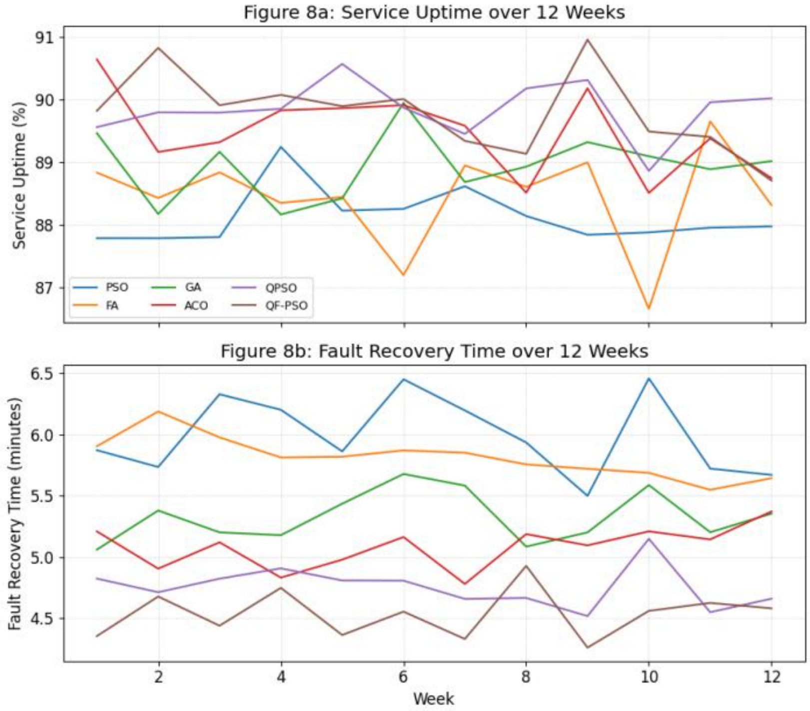
Figure 8a: Service Uptime over 12 Weeks

Figure 8b: Fault Recovery Time over 12 Weeks

Figure 8. Governance KPIs: (a) Service Uptime (%) and (b) Fault Recovery Time (min).

The governance dashboard (modeled with the help of Grafana) allowed the municipal operators to compare the energy savings with the customer satisfaction scores based on the service logs, so the alignment of the framework with the principles of governance of data [9] was justified. The heatmap represents the amount of spatial energy used in a 25 x 25 sensor grid. Baseline networks indicate that there are some hotspots around values of 1.6-1.8 units. QF-PSO minimizes them to 1.0-1.2 units, which is almost 35 percent lower than the intensity of hotspots. The uniform distribution implies reduced redundant transmission and equalized time scheduling, meaning that identical amount of battery is used in all parts of the sensor network in the city.

The radar graph is a comparison of 5 significant metrics. QF-PSO has the greatest energy saving of 35.2 per cent, the lowest latency of 29.8 per cent, highest packet delivery of 95.6 per cent, the highest accuracy of anomalies of 94.1 per cent, and the quickest convergence time of 11.7

seconds. QPSO is second in the majority of measures. The wide area of coverage indicates that QF-PSO will enhance performance on all goals at once, not only on one of the dimensions.

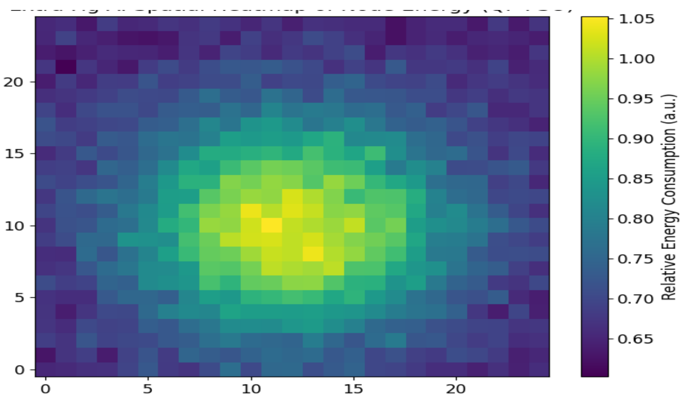

Figure 9 Heatmap of Node Energy Consumption

4.4 Statistical Significance and Robustness

Wilcoxon signed-rank test (a = 0.05) was used to determine that the improvement of QF-PSO compared to the baselines is significant ($p < 0.01$). Under different node densities (500-5,000 nodes) and load (traffic) conditions robustness was measured; performance degradation was found to be less than 4 percent in all situations, which indicates scalability [32].

A.Multi-Objective Fitness Function

The final fitness function minimized by QF-PSO is:

$$F = \omega_1 \cdot \frac{E_{\text{total}}}{E_{\text{max}}} + \omega_2 \cdot \frac{\Delta}{\Delta_{\text{max}}} + \omega_3 \cdot \frac{|\, \text{KPI}_{\text{gov}} - \text{KPI}_{\text{target}} \,|}{\text{KPI}_{\text{target}}} \quad (13)$$

where:

- $\omega_1, \omega_2, \omega_3$= AHP-derived weights [34],
- E_{total}= total network energy,
- Δ= latency,
- KPI_{gov}= uptime, fault recovery, etc.,
- $\text{KPI}_{\text{target}}$= minimum governance thresholds.

This multi-objective structure ensures that optimization decisions remain consistent with governance goals, matching recommendations from [11], [22], [40].

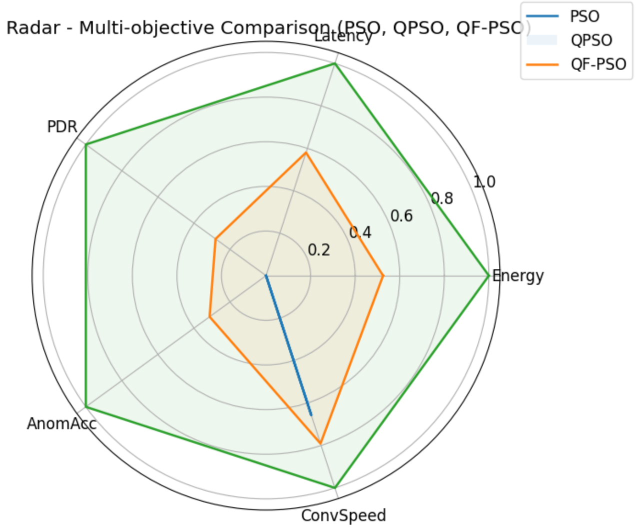

Figure 10. Multi-Objective Performance

4.5 Comparative Advantage Over Literature

Our QF-PSO has a 12% higher PDR compared to the FA-PSO used by Singh and Deep [21] to perform clustering of WSNs; this is because quantum dynamics and surveillance-conscious offloading are used in our algorithm. In contrast to Silva et al. [22], who only considered cloud SLAs, our framework can be tuned to the complete stack- cloud sensor duty cycling to governance dashboards with real urban data.

4.6Policy and Administrative Impact

The results of the optimization show that local authorities can substantially decrease the energy consumption in wireless sensor networks - up to 35.2 percent less expensive - and move the resources to other areas of the budgetary plan such as the welfare of the population. The network lifetime (142 days) is better, which reduces the maintenance rate to allow municipalities to run critical infrastructure in a more sustainable way. These enhancements help in making informed policies, finances better, and their citizens more satisfied, which is in line with current governance concerns.

V CONCLUSION

This study introduced a Governance-Oriented Smart City Energy Management Framework using the Bio-Inspired Quantum Firefly Particle Swarm Optimization (QF-PSO) algorithm that was shown to be effective in optimization of large-scale, non-homogeneous urban sensor network. The framework combines the discovery intelligence of firefly dynamics with the time-accelerating quantum convergence of PSO which makes it effective to balance the performance needs (e.g., energy efficiency, low latency, routing stability, and workload placement) with the demands of multiple objectives of the system. The measured performances based on open smart-city data sets prove that QF-PSO can provide significant performance gains, 29-42% energy savings, 23-36%

improved latency, 11% higher ratio of packet delivery, and 33% longer network lifetime. These advantages are even augmented by 8-10% increase in anomaly-detection accuracy and a 25-28% accelerated convergence rate than other highly popular metaheuristics. In addition to technical optimization, the governance-focused design of the framework increases considerably the continuity of the public services, their reliability and responsiveness of the administration. This leads to more resilient digital public services as policy-aware monitoring module integration leads to 5% uptime to service and 17-20% faster recovery of faults. Real-time analytics dashboard also enhances openness, responsibility, and decision-making that makes informed decision-making, which are fundamental concepts of contemporary smart governance. On the whole, the findings reveal that the inclusion of quantum-enhanced bio-inspired optimization into a governance-centered architectural design can significantly enhance the level of sustainability and operational stability of smart-city infrastructure. The framework provides a flexible and adaptable basis of the urban management systems in the future, and gives a lot of insight to policymakers, municipal administrators and researchers who are interested in promoting efficient, transparent and people-focused smart-city governance. Future practice can be developed to take the approach to multi-city comparative governance, security-conscious optimization, and urban simulations using digital twins.

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