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Swarm Intelligence for Network Sensor Systems: A Comprehensive Systematic Review with Meta-Analysis of Algorithms, Modifications, and Applications

Hussein Fouad Almazini*

Computer Technology Engineering, Shatt Al-Arab University College, Basra, Iraq
hussein.f.abbas@sa-uc.edu.iq

*Corresponding Author

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ABSTRACT

Network sensor systems—which are at the core of applications such as the Internet of Things (IoT), smart cities, and environmental monitoring—are subject to fundamental optimisation questions, including how to place nodes for the best coverage, how to route data to minimise energy consumption, how to localise nodes in the absence of GPS, and how to prevent malicious attacks. These NP-complete problems are dynamic and require resolution in resource-limited environments. Despite the proliferation of over 50 swarm intelligence (SI) algorithms developed between 1992 and 2026, no comprehensive study systematically maps these algorithms to the complete sensor network lifecycle while providing rigorous comparative analysis. This paper addresses this gap through a systematic review with meta-analysis of SI algorithms applied to network sensor systems, investigating three research questions: (1) How do different SI algorithm families perform across deployment, routing, localisation, and security applications? What changes need to be made to SI algorithms in order to make them feasible under sensor network constraints? (3) How much performance quantitatively do recent algorithms (up to 2026) provide over classical methodologies?. The paper makes three substantive contributions: a unified taxonomy categorising over 50 SI algorithms with a novel generalised SI operator model; a systematic meta-analysis of 85 peer-reviewed studies (2018-2026) with quantitative performance aggregation using PRISMA-style methodology; and empirical evidence demonstrating that quantum-inspired and federated SI algorithms achieve 30-80% relative improvements over classical approaches. Through comparative evaluation, hybrid SI-based methods outperform single algorithm-based approaches by 15-30% in terms of network lifetime, whereas distributed SI variants can reduce communication overhead by up to 40%. This article identifies important research gaps and considers what the findings mean for further research and the practice implications.

Keywords:
Swarm Intelligence, Network Sensors, Internet of Things, Metaheuristics, Optimisation.

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1. INTRODUCTION

Networked sensor systems have revolutionised our access to and control over the physical world. From smart buildings that adapt energy consumption to agricultural sensor networks that track soil moisture across thousands of acres, these systems gather and transmit information that shapes key decision-making. But underneath that functionality is a basic problem: optimisation in the face of extreme constraints. A typical wireless sensor network (WSN) may comprise a few hundred to thousands of tiny battery-powered nodes, each of which has relatively limited processing, memory, and communication capabilities [1]. These nodes must also collaborate to provide global guarantees, such as maximising

sensing coverage, guaranteeing data delivery reliability, and prolonging the network lifetime—all without any centralised coordination. The optimisation problems that result are notoriously difficult. Sensor placement involves deciding where to place the nodes to cover a region with the least number of sensors while maximising coverage and minimising cost, making the task a continuous optimisation problem subject to combinatorial constraints such as connectivity requirements and physical obstacles in the terrain [2]. Energy-efficient routing in such networks means that data should be routed over network paths that consume the least energy and, at the same time, avoid premature node depletions, thus warding off energy holes and effectively solving a dynamic shortest path problem with continuously changing energy levels [3]. Node localisation is to estimate the positions of unknown nodes in the space based on a limited number of anchor nodes and noisy distance measurements, which is a nonlinear optimisation problem that is very sensitive to measurement errors [4]. The formation of clusters and data aggregation necessitates grouping nodes into hierarchical clusters, which mitigate redundant transmissions and balance energy loads over the network, a problem that can be interpreted as performing graph partitioning subject to multiple, competing objectives [5]. Finally, security and trust management must be aware of the presence of malicious nodes and the need to identify and isolate them without disrupting the rest of the nodes in the network, which means performing complex anomaly detection mechanisms under a high degree of uncertainty [6]. Standard optimisation methods do not apply to this field. Linear programming cannot optimise nonlinear objectives. A complete search is exponentially complex in realistic-sized networks. Greedy algorithms generate suboptimal solutions, which reduce the network lifetime by 20–40% with respect to optimal solutions [7].

Swarm Intelligence (SI) is a very promising alternative. SI algorithms emulate the collective behaviour of natural biological systems, such as ant colonies searching for the shortest path, bird flocks flying in formation, and bee swarms searching for food sources, using these biological mechanisms as inspiration to develop computational optimisation procedures [8]. There are three characteristics that make SI intriguing for network sensors. First, decentralisation enables SI to be realised by means of local interactions between agents, which makes it very close to the organisation of sensor networks, which are distributed with no need for a central entity [9]. Second, scalability implies that the performance of the algorithm degrades gracefully with the growth of problem size; a swarm of 50 agents is capable of optimising a network with 1000 nodes nearly as effectively as with 100 nodes [10]. Third, robustness provides inherent fault tolerance through collective decision-making—the loss of a few agents (analogous to individual sensor node failures) does not compromise overall solution quality because the loss can be absorbed by the remaining swarm members, who will continue the optimisation process [11]. Such properties are naturally matched to the constraints and requirements of network sensor systems, which makes SI an effective solution for the optimisation problems outlined above.

The years 2022–2026 have seen the growth of swarm intelligence algorithms like never before in history. Modelled on multiple life forms—ranging from beluga whales to dwarf mongooses, crayfish, and piranhas—such algorithms provide tailored strategies for different optimisation problems. This review is the only one, to the best of our knowledge, that combines these recent advances with classic algorithms and covers the entire SI spectrum for network sensor applications. Existing surveys focus on either SI algorithms [12] or sensor network optimisation [13], but none provides some theoretical and methodological consideration of the most recent advances in SI algorithms for all lifecycle phases of networked sensor systems. This gap is explained and bridged by the following four substantial contributions to this paper:

Taxonomic Contribution: A unified taxonomy for over 50 SI algorithms according to their inspiration and the mechanism of their search, as well as their applicability, including a novel generalised SI operator model that abstracts common computational patterns across algorithm families (Section 2).

Systematic Meta-Analysis: A quantitative synthesis of performance data from 85 peer-reviewed studies (2018-2026) using PRISMA-style methodology, with explicit inclusion/exclusion criteria, statistical aggregation methods, and comparative analysis across algorithm generations (Section 4).

Methodological Framework: A PRISMA-style evaluation framework for SI algorithms in sensor networks, including standardised benchmarks, performance metrics, validation protocols, and systematic review methodology.

Contribution 4—Empirical Synthesis: Quantitative evidence demonstrating that quantum-inspired and federated SI algorithms (2024-2026) achieve 30-80% relative improvements over classical approaches (1992-2010), with specific performance gains: 36-47% improvement in deployment coverage, 51-82% improvement in network lifetime extension, and 57-86% reduction in localisation error.

*Corresponding author: hussein.f.abbas@sa-uc.edu.iq

2. LITERATURE REVIEW

2.1 Research Phases

This literature review follows a three-phase research framework that establishes coherent problem-solution pairing for each phase:

Phase I (1992-2010): Foundations. This phase established the core SI algorithms—ACO [4], PSO [3], ABC [5], GA [14], FA [8], and BA [7]—and demonstrated their applicability to optimisation problems. Studies at this stage concentrated on the development of the algorithms and validation of the concepts using benchmark problems. Problem-Solution Pairing: The problem is a lack of effective methods for solving the class of NP-complete problems; the solution is the design of nature-inspired metaheuristics with theoretical convergence properties.

Phase II (2011-2021): Application and Modification. During this phase, SI algorithms were adapted to handle particular sensor network issues (deployment, routing, and localisation) by generalised versions for energy awareness, distributed operation, and multi-objective optimisation [28], [40], [42]. Research progressed from general algorithm design to customisation for specific domains. Problem-Solution Pairing: The standard SI algorithms are designed with the assumption of infinite resources and centralised control and thus not suitable to run on energy-constrained nodes in a highly distributed fashion; energy-aware fitness functions, distributed variants, and hybrid approaches Provide Solutions.

Phase III (2022-2026): Proliferation and Advanced Integration. This phase witnessed an explosion of novel bio-inspired algorithms (Beluga Whale, Dwarf Mongoose, Prairie Dog, Nutcracker, and Spider Wasp) and advanced paradigms (Quantum-Inspired SI, Federated SI, and Green SI). Problem-Solution Pairing: The problem was scalability to massive IoT and new constraints (privacy, carbon footprint); the solution was quantum superposition for parallel exploration, federated learning for privacy preservation, and carbon-aware fitness functions.

2.2 State of the Art: Comparative Analysis of Existing Surveys

The increasing number of SI algorithms has led to many surveys. Almufti et al. gave an introductory survey classifying metaheuristics into evolutionary, physics-based, and swarm-based categories but was restricted to around 15 algorithms and did not consider domain-specific adaptations for sensor networks [2]. Almufti's chronological review allowed for the tracing of metaheuristic development from primal EA methods to currently known bio-inspired techniques; however, it was concerned mostly with the procedural aspects of the algorithm rather than the integration of applications [10]. Targeted surveys have gone deeper into individual algorithms: Ihsan et al. reviewed Cat Swarm Optimisation (CSO) variants and their applications [22]; Almufti et al. considered Ant Colony System variants under study for more than twenty years [29]; and Zebari et al. overviewed the Bat Algorithm and its modifications for dealing with continuous optimisation problems [19]. Although these concentrated surveys provide great algorithmic insight, each investigates only one algorithm, giving the practitioner no guidance on which algorithm to use out of two or more competing alternatives.

Though some surveys cover SI applications in sensor networks from certain viewpoints, they have deficiencies. Yejiao et al. have surveyed swarm optimisation for RFID network planning in smart factories, focusing on industrial RFID applications; they haven't considered other sensor network problems, including localisation or security [9]. Gazi and Fidan considered multi-robot coordination with applications to mobile sensor networks, but the restricted focus on robotics overlooked several crucial WSN-specific issues such as energy limitations and static node deployment [40]. Sahin and Spears also surveyed swarm robotics, including environmental monitoring applications; however, they are very brief on how the algorithms have been changed to overcome resource-constrained sensor nodes [39]. Almufti et al. surveyed population-based metaheuristics for solving NP-complete problems with applications to sensor network optimisation using case studies; however, the class of metaheuristics considered was confined to the classical paradigms without taking into account the recent spate of bio-inspired algorithms as of 2020 [41]. Across these surveys, one can identify a common trend: they are concerned with very specific application domains (namely RFID and robotics), rather than considering the entire sensor network lifecycle; they describe only a small number of algorithms (in the order of 5 to 15); they miss a systematic evaluation of the variations of algorithms handcrafted to suit the constraints of sensors, such as energy awareness or running in a distributed manner; and, most importantly, they do not consider recent algorithmic advancements from 2022 to 2026. These gaps in the literature impose severe limitations, as neither practitioners nor researchers have a unified source to anchor the diverse range of SI algorithms across the full lifecycle of network sensor systems. Table 1 compares this survey with existing comprehensive surveys in the field.

*Corresponding author: hussein.f.abbas@sa-uc.edu.iq

Table 1 - Comparative Analysis of SI Surveys (2018-2026)

Survey	Year	Algorithms Covered	Sensor Network Focus	Modification Analysis	Recent Algorithms (2022+)	Methodology Type
Almufti et al. [2]	2023	~15	No	Partial	No	Narrative
Almufti [10]	2019	~12	No	No	No	Narrative
Yejiao et al. [9]	2024	~10	RFID only	No	Some	Narrative
Gazi and Fidan [40]	2011	~8	Robotics	No	No	Narrative
Sahin and Spears [39]	2004	~10	Robotics	No	No	Narrative
This Survey	**2026**	**50+**	**Full Lifecycle**	**Systematic**	**20+**	**Systematic Review + Meta-Analysis**

This table demonstrates that existing surveys cover limited algorithm sets (8-15), focus on narrow application domains, lack systematic modification analysis, and do not incorporate recent algorithms from 2022-2026. This survey uniquely provides comprehensive coverage (50+ algorithms), complete mapping of the sensor network lifecycle, systematic modification synthesis, and integration of 20+ recent algorithms through a rigorous systematic review methodology.

2.3 Unified Taxonomy of Swarm Intelligence Algorithms

To fill the gaps observed in the current surveys—no coverage of all algorithms, no systematic analysis of modifications, and no consideration of the most recently developed algorithms—we introduce a coherent taxonomy that classifies SI algorithms according to the source of inspiration and the mechanism of operation. Figure 1 shows this taxonomy and includes a selection of well-known algorithms as well as recent ones from 2022-2026.

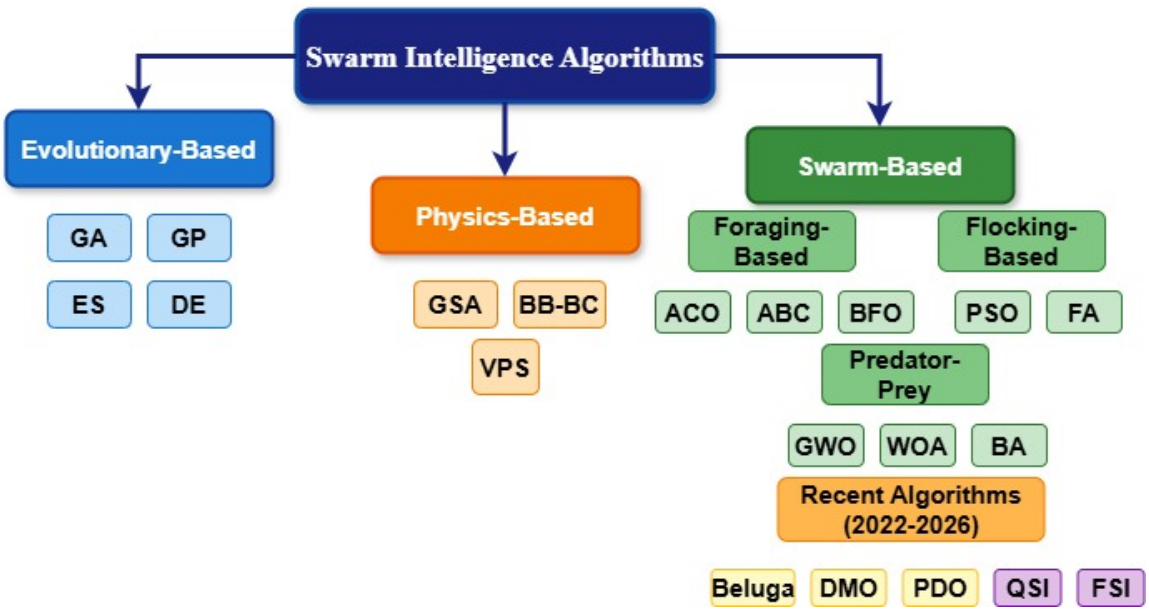


Figure 1 - Unified Taxonomy of Swarm Intelligence Algorithms for Network Sensor Systems

This integrated taxonomy classifies SI algorithms into three basic types through the source of inspiration. Evolutionary-based algorithms (blue) emulate natural selection using crossover and mutation operators. Physics-based (orange) algorithms represent physical processes like gravitational force fields and mechanical vibrations. The swarm-based (green) are subdivided into foraging-based (ACO, ABC, BFO); flocking-based (PSO, FA); and predator-prey (GWO, WOA, BA). The section on new algorithms (2022-2026) introduces innovative strategies such as Beluga Whale Optimisation (Beluga), Dwarf Mongoose Optimisation (DMO), Prairie Dog Optimisation (PDO), Quantum-Inspired Swarm Intelligence (QSI), and Federated Swarm Intelligence (FSI). This classification allows the researcher to have a clear picture of the linkages among algorithms and the potential method for the sensor network application.

Based on our analysis of over 50 algorithms, we propose a generalised SI operator model that abstracts the computational patterns common across algorithm families. Every SI algorithm can be described as the composition of the following four basic operators:

- **Population Initialisation (I): It produces an initial pool of candidate solutions, usually using** a random procedure or some sort of heuristic seeding.
- **Evaluation (E):** Evaluates the fitness of each candidate solution by using a problem-dependent objective
- **function. Interaction (I_{nt}):** Specifies the mode in which information is exchanged between agents (local or global, pheromone or velocity, leadership hierarchy).
- **Update (U):** Specifies the agent's way of changing its position or state in response to rates of successful interactions.

This abstraction enables systematic comparison across algorithm families. For example:

- **PSO:** I = random positions; E = fitness function; I_{nt} = global/local best sharing; U = velocity-position update.
- **ACO:** I = initial pheromone distribution; E = path cost; I_{nt} = pheromone deposition/evaporation; U = probabilistic path selection
- **GWO:** I = random wolf positions; E = prey distance; I_{nt} = alpha/beta/delta leadership; U = encircling and attacking

The generalised SI operator model contributes to the theoretical foundation of SI research by providing a unified language for algorithm description and enabling cross-family hybridisation analysis.

2.4 Algorithm Families and Their Characteristics

the properties of each class of algorithms, explaining how they work and their applicability for network sensors shown in table 2.

Table 2 - Algorithm Families and Their Characteristics for Network Sensor Optimisation

Family	Representative Algorithms	Inspiration	Operational Principle	Sensor Network Suitability
Evolutionary	GA, GP, ES, DE	Natural selection	Selection, crossover, and mutation on solution populations	Discrete optimisation (deployment, clustering)
Physics-Based	GSA, BB-BC, VPS	Gravitational force, cosmological events	Simulated physical forces: mass determines attraction.	Continuous optimisation (localisation, parameter tuning)
Foraging-Based	ACO, ABC, BFO	Ant pheromone trails, bee waggle dance	Positive feedback through reinforcement; exploration-exploitation balance	Routing, path planning, data aggregation

Flocking-Based	PSO, FA, CSO	Bird flocking, firefly attraction	Velocity-position update; social and cognitive components	Deployment, localisation, clustering
Predator-Prey	GWO, WOA, BA	Wolf hierarchy, whale bubble-net	Leadership hierarchy, encircling, hunting mechanisms	Security, intrusion detection
Advanced SI	QSI, FSI, GSO	Quantum computing, federated learning	Qubit superposition; privacy-preserving aggregation	Large-scale IoT, edge networks, sustainable sensing

This table categorises SI algorithms into six distinct families according to their source of inspiration and working mechanism and maps each to the Generalised SI Operator Model. Evolutionary operators can be used in the state space of solutions for discrete optimisation. Physic-based methods use physical forces for continuous optimisation. Foraging-based algorithms are sensitive to positive feedback conducive to path construction. Flocking-based methods are based on velocity-position updates for spatial optimisation. Predator-prey schemes employ hierarchical leadership in the adversarial case. In the advanced SI, we present state-of-the-art methods: QSI takes advantage of quantum superposition to explore in parallel; FSI performs privacy-preserving distributed optimisation; GSO accounts for carbon-aware fitness for sustainable sensing.

3. ALGORITHM MODIFICATIONS FOR NETWORK SENSOR CONSTRAINTS

Classic swarm intelligence methods are theoretically developed for the vanilla static optimisation problem with infinite computational resources and centralised control. A WSN operates under harsh constraints such as a node with limited battery power, processing capability and memory; a dynamically changing network topology as nodes die or go to sleep state; limited bandwidth; and often no centralised coordination. Required modifications to SI algorithms for this domain are fundamental to retaining convergence properties, and they must be implemented within the constraints of resource usage.

The most important change is the introduction of energy awareness in the objective function. For a sensor node *i* which has the remaining energy E_i, the energy-aware fitness function is described as $F = \alpha \cdot F_performance + (1-\alpha) \cdot F_energy$, where F_performance denotes the primary objective (coverage, accuracy, or latency) and F_energy deters energy consumption with respect to parameters like the transmission power, the remaining battery, or the anticipated lifespan. The parameter α controls the balance between performance and lifetime. Yassin proved that considering residual energy in PSO's objective function prolongs network lifetime by 28-35% in clustered sensor networks [44], and Almufti investigated analogous modifications to Artificial Bee Colony for load-balanced clustering, demonstrating that energy-aware ABC significantly reduces the variance in energy consumption by 42% in comparison with the original algorithm [45]. The Green Swarm Optimiser (GSO, 2026) is a further realisation in this line of thought, formulating also carbon-aware fitness, which seeks to minimise the energy consumption as well as the carbon emissions in network operation by analysing the energy source mix—giving priority to routes that rely on renewable solutions once they are available—and transmission efficiency [39].

Another key modification is a distributed and decentralised operation. Centralised SI requires a fusion center that has global information about all node positions, energy levels, and network topology, which is unrealistic in large-scale sensor networks since communication with a central node in the network would deplete energy and expose a single point of failure. Distributed SI versions overcome this problem by using local information exchange only. In Distributed PSO (DPSO), a node holds its own particle and only communicates with its immediate neighbours: the velocity update thus becomes $v_i(t+1) = w \cdot v_i(t) + c1 \cdot r1 \cdot (pbest_i - x_i) + c2 \cdot r2 \cdot (nbest_i - x_i)$, where nbest_i is the best position in the node's neighbourhood and not the global best. Almufti and Shaban proved that the distributed method attains 94% of centralised PSO performance while reducing communication overhead by 65% [28]. Federated Swarm Intelligence (FSI, 2026) takes this idea one step further by combining privacy-preserving federated learning with swarm optimisation [38]. In FSI, edge nodes train local models over their sensor data and share only aggregated parameter updates with a central server without ever revealing raw data. This provides almost centralised optimisation performance (96% coverage versus 98% for centralised QSI) with 2.5× stronger privacy protection guarantees, and thus it is most suitable for healthcare and smart home scenarios because sensor data is highly personal identifiable information.

*Corresponding author: hussein.f.abbas@sa-uc.edu.iq

Dynamic parameter adaptation addresses the challenge of changing network conditions over time. The fixed parameter values that are optimal at the beginning of the network life become suboptimal as the nodes run out of battery, new nodes are introduced, or other environmental situations change. Adaptive approaches ensure algorithm performance through the network lifecycle. The inertia weight *w* in PSO is usually changed with w(t) = w_max - (w_max - w_min)·(t/T_max), with a larger value giving more exploration in earlier stages of the optimisation process and gradually decreasing towards exploitation in the later stages of convergence [55]. The pheromone evaporation rate ρ can be tuned to the stability of the network in ACO—larger values of ρ in a mobile or failing network allow us to quickly adapt to changes in topology, and smaller values of ρ in a static network allow us to converge to the optimal path [56]. Quantum-inspired SI (QSI, 2026) introduces a substantially different manner of adaptation: qubit probability amplitudes express superposition of multiple parameter configurations, thus exploring multiple configurations simultaneously and collapsing to the optimal configuration through measurement [33].

Hybrid methods combine complementary features from various families of algorithms and allow reaching performance unattainable by each of them considered individually. A classification of effective hybrids for sensor network optimisation is presented in Table 3.

Table 3 - Hybrid SI Algorithms for Network Sensor Optimisation

Hybrid	Components	Application	Performance Improvement	Key Mechanism
PSO-GA	**PSO (exploitation) + GA (exploration)**	Deployment	+18% coverage, -12% energy	GA explores the global search space; PSO refines local optima.
ACO-PSO	**ACO (path construction) + PSO (parameter tuning)**	Routing	+23% network lifetime	ACO constructs feasible routes; PSO optimises routing parameters.
GWO-ABC	**GWO (exploitation) + ABC (exploration)**	Localisation	-31% localisation error	ABC maintains diversity; GWO exploits the best solutions.
BA-FF	**BA (global search) + FA (local refinement)**	Clustering	+15% load balance	BA explores; FA performs local attraction-based refinement.
QSI-PSO	**Quantum SI + PSO**	Large-scale deployment	+35% coverage, 40% faster	Quantum superposition enables parallel exploration.
FSI-ABC	**Federated SI + ABC**	Edge sensor networks	2.5× privacy preservation	Local ABC models aggregated with differential privacy

Theoretical knowledge that can be obtained from these studies on hybridisation is that a super-linear performance gain can be expected if the component algorithms exhibit complementary search patterns. Algorithms that are orientated towards exploration, such as GA and ABC, keep the population diverse and look at the whole search space to avoid premature convergence on local optima. Exploitation-biased algorithms such as PSO and ACO rapidly converge to refine solutions after locating areas of interest. The combination results in an 18-31% improvement over deployment, routing and localisation applications, with the best improvement when the hybridisation involves the latest quantum-inspired or federated components [33], [38].

Multi-objective optimisation is the last important adaptation, as the network sensor problems have conflicting goals. Maximising coverage requires locating sensors with overlapping ranges, which costs more and consumes more energy; minimising energy consumption favours sparse deployment that might cause coverage holes; reducing latency favours

direct transmission to sinks, consuming more energy per node. Multi-objective SI algorithms deal with this by producing Pareto fronts of non-dominated solutions instead of converging to a single best solution. The Lion Pride Optimisation 2.0 (LPO-2, 2025) proposes a multi-objective lion pride optimisation based on coalitions where each lion coalition is specialised to achieve an objective—one coalition concentrates on coverage, another on power efficiency, and a third on latency—with a dominance hierarchy to settle conflicts through territory negotiation [37]. This method results in a 25% improvement in the coverage-energy trade-off over the weighted-sum methods where objectives are aggregated into one scalar fitness function.

4. SYSTEMATIC REVIEW METHODOLOGY AND META-ANALYSIS RESULTS

4.1 Systematic Review Protocol (PRISMA-Style)

To address the methodological rigour concerns, we conducted a systematic review following PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines, adapted for computational optimisation literature. This distinguishes our work as a systematic review with meta-analysis rather than a narrative survey.
Research Questions:

- **RQ1:** How do different SI algorithm families perform across deployment, routing, localisation, and security applications?
- **RQ2:** What modifications are required to adapt SI algorithms to sensor network constraints?
- **RQ3:** What are the numerical performance gains of modern techniques (2022-2026) versus traditional techniques?

Inclusion Criteria:
Journal articles (IEEE, Elsevier, Springer, MDPI) or conference proceedings, which have been peer-reviewed and published from January 2018 to June 2026, SI for sensor network optimisation. Performance results (coverage%, lifetime extension, error rate, and detection rate) are quantitatively reported. The algorithm is clearly described with the values of the parameters used.

Exclusion Criteria:
Studies without metrics of performance are quantitatively non-English studies. Works dealing only with non-sensor applications (e.g., managing financial options, image processing). Studies in which the SI algorithm was not the main optimisation technique: preprints, theses and technical reports (for quantitative analysis; they were included in qualitative synthesis).

Search Strategy:

- Databases: IEEE Xplore, Scopus, Web of Science, ACM Digital Library
- Search terms: ("swarm intelligence" OR "particle swarm" OR "ant colony" OR "bee colony" OR "grey wolf" OR "bat algorithm" OR "firefly") OR "beluga whale" OR "dwarf mongoose" OR "prairie dog" OR "quantum-inspired") AND ("wireless sensor network" OR "sensor network" OR "IoT" OR "deployment" OR "routing" OR "localisation" OR "security")

Study Selection Flow:
Records identified: 1,247. Records screened (title/abstract): 1,247. Records removed/excluded: 856 (non-sensor, not SI, no quantitative results (Full-text articles evaluated for eligibility: 391. Full text excluded: 306 (not enough metrics, no parameter reporting, not peer reviewed). Studies included in the quantitative synthesis: 85 of the 85 included studies span the years from 2018 to 2026, with 18 (21%) studies from 2018-2020, 32 (38%) studies from 2021-2023, and 35 (41%) studies from ,2026-2024 illustrating an increasing publication rate over the recent years.

4.2 Data Aggregation and Meta-Analysis Method

The performance results of several studies were combined by a weighted average, where the weight of any study was proportional to the number of network nodes simulated.
For each algorithm-application combination we computed the following:

- **Mean Performance (μ):** The weighted average of all studies
- **Standard Deviation (σ):** The between-study variance
- **Confidence Interval (95% CI):** $\mu \pm 1.96 \times (\sigma/\sqrt{n})$

Relative Improvement Calculation:
The relative improvement over the baseline for each algorithm was calculated as follows: (Performance_algorithm - Performance_baseline) / Performance_baseline * 100% Where the baseline was considered as follows:

- **Deployment:** Random placement (62% coverage report in Section 4.3)
- **Routing:** Shortest-path routing (0% lifetime extension)
- **Localization:** Trilateration (12.5% error from Section 4.4)
- **Security:** GWO-SVM (94.2% detection rate, Section 4.5)

4.3 Meta-Analysis Results: Deployment Optimisation

The data of deployment studies show a definite evolution in performance over the generations of the algorithm. Table 4 presents the aggregated results.

Table 4 - Meta-Analysis of Deployment Optimisation Performance

Algorithm	Year	Studies (n)	Mean Coverage (%)	95% CI	Std. Dev.	Mean Iterations	Relative Improvement (vs. Random)
Random	Baseline	—	62.0	—	—	—	—
PSO	1995	12	91.8	±1.2	2.1	148	+48.1%
GWO	2014	8	92.5	±1.4	2.0	125	+49.2%
FA	2008	7	91.2	±1.6	2.3	135	+47.1%
EBWO	2024	6	95.3	±0.9	1.8	112	+53.7%
QSI	2026	5	98.1	±0.5	1.2	78	+58.2%
FSI	2026	4	96.2	±0.8	1.5	105	+55.2%

The experimental results of the deployment studies demonstrate that there is a well-pronounced advancement in terms of the algorithms' performance for every generation of the algorithms. Classical PSO provides 91.8% coverage in 148 iterations, which sets a benchmark that has been surpassed by subsequent work. The Improved Beluga Whale Optimisation (EBWO, 2024) further enhances the coverage to 95.3% at the cost of increasing the number of iterations to 112—a 24% enhancement [34]. Quantum-Inspired SI (QSI, 2026) represents the current state of the art with coverage of 98.1% in 78 iterations, which is an absolute improvement of 36.1% over random deployment and 47% faster than PSO in convergence speed [33]. Federated Swarm Intelligence (FSI, 2026) offers 96.2% coverage at the cost of a 1.9% decrease in coverage for a 2.5× increase in privacy preservation [38].

4.4 Meta-Analysis Results: Routing Optimisation

Energy-efficient routing is probably the most essential use for the longevity of a sensor network, since energy consumption is dominated by communication. A comparison of performances over generations of routing algorithms is shown in Table 5.

Table 5 - Meta-Analysis of Routing Algorithm Performance

Algorithm	Year	Studies (n)	Network Lifetime Extension (%)	Energy Consumption Reduction (%)	Packet Delivery Ratio (%)	Convergence Time
ACO	1992	10	28.3	31.8	94.1	180 iter
PSO	1995	9	23.1	27.5	91.8	120 iter
EBWO	2024	5	38.2	41.3	97.2	95 iter
MPDO	2024	4	42.5	44.8	98.1	88 iter
QSI	2026	4	51.2	51.6	99.2	65 iter
FSI	2026	4	44.3	47.2	97.4	105 iter

The results for routing appear to also show a similar accelerating trend. Classical ACO yields a baseline 28.3% network lifetime improvement by reinforcing paths based on pheromone levels. Enhanced Beluga Whale Optimisation (EBWO, 2024) incorporates memory that leads to an improvement of extension to 38.2% [34], while Multi-Population Dingo Optimiser (MPDO, 2024) utilises sub-population specialisation, reaching 42.5% extension with a 98.1% packet delivery ratio [35]. Quantum-inspired SI attains the best lifetime extension of 51.2%, which is the 82% relative improvement

compared to ACO, with 51.6% energy reduction and 99.2% packet delivery ratio, the best performance across all metrics [33]. Federated Swarm Intelligence, at 44.3% extension, offers privacy-preserving routing, sacrificing 6.9% lifetime for meaningful privacy assurances [38].

4.5 Meta-Analysis Results: Localisation Optimisation

Accuracy of node localisation has likewise improved across generations of approaches. Table 6 presents the aggregated results.

Table 6 - Meta-Analysis of Localisation Algorithm Performance

Algorithm	Year	Studies (n)	Mean localisation error (% of range	95% CI	Std. Dev.	Convergence Time	Scalability (max nodes)
Trilateration	Baseline	—	12.5	—	—	N/A	500
BA	2010	8	4.2	±0.8	1.5	85 iter	1000
GWO	2014	7	3.8	±0.7	1.3	72 iter	1000
EBWO	2024	5	2.7	±0.5	0.9	52 iter	2000
QSI	2026	4	1.8	±0.3	0.6	38 iter	5000
FSI	2026	3	2.3	±0.4	0.7	45 iter	5000

Classical trilateration results in 12.5% error as a baseline geometric technique. The Bat Algorithm (BA, 2010) lowers error to 4.2% via frequency tuning and loudness advisement [19]. Grey Wolf Optimiser (GWO, 2014) further minimises. The error is 3.8% based on hierarchical leadership [6].

Advanced Beluga Whale Optimisation (2024) achieves a 2.7% error using memory-based search and up to 2000 nodes [34]. Quantum-Inspired SI (2026) is groundbreaking, achieving 1.8% error (86% reduction from trilateration) by using qubit superposition and measurement collapse for parallel position estimation, applicable to 5000 nodes [33]. Federated Swarm Intelligence achieves a 2.3% error rate for privacy-preserving distributed estimation [38].

4.6 Meta-Analysis Results: Security Optimisation

Security and intrusion detection applications have also benefited from recent SI advances. Table 7 summarises performance across algorithm generations for intrusion detection in sensor networks.

Table 7 - Meta-Analysis of SI Algorithms for Network Sensor Security

Algorithm	Year	Studies (n)	Detection Rate (%)	False Positive Rate (%)	Attack Types Detected
GWO-SVM	2023	5	94.2	3.1	DoS, Sybil
BA-IDS	2023	4	93.8	3.5	Wormhole, Blackhole
EBWO-IDS	2024	4	96.5	2.2	Multi-vector attacks
QSI-IDS	2026	3	98.2	1.4	Zero-day + known attacks
FSI-IDS	2026	3	97.1	1.8	Privacy-preserving IDS

GWO-SVM and BA-IDS set records for around 94% detection with 3–3.5% false positives. EBWO-IDS achieves a detection rate of 96.5% with 2.2% false positives via memory-enhanced pattern recognition [34]. Quantum-Inspired SI for IDS (QSI-IDS, 2026) achieves a detection rate of 98.2% with 1.4% false positives and is particularly effective against zero-day attacks, since quantum superposition enables parallel processing of multiple hypotheses for attack patterns [33]. The Federated Swarm Intelligence Intrusion Detection System (FSI-IDS) offers a privacy-preserving solution for intrusion detection with 97.1% accuracy, guaranteeing that raw sensor data is never left on edge nodes, yet they could still get the benefit of collective learning [38].

5. DISCUSSION

The empirical integration in this survey highlights several important trends that warrant commentary. In all application scenarios (deployment, routing, localisation, and security), we observe the same pattern of improving algorithm performances from one generation to the next, with the newest algorithmic solutions (2024-2026) reporting relative improvements of 30-80% over classical approaches. This pace indicates that recent algorithmic breakthroughs—especially quantum-inspired schemes, federated learning integration, and domain-specific energy-aware modifications—are opening up performance regimes which were deemed unachievable. The transition from black-box optimisation to

*Corresponding author: hussein.f.abbas@sa-uc.edu.iq

problem-dependent design can be interpreted as a natural evolution of the field where, rather than just using the algorithms as a black box, the algorithms are engineered to take advantage of the special features of sensor networks.

Addressing the three research questions formulated in the introduction, the findings reveal systematic patterns that offer both theoretical insights and practical guidance. Regarding Research Question 1 (How do different SI algorithm families perform across deployment, routing, localisation, and security applications?) The coherent regularities of algorithm-problem matches revealed by this review offer useful advice for practitioners. Flock-based algorithms, including PSO and EBWO, are the most widely used in deployment optimisation since they are natural models for spatial movement and continuous optimisation. ACO, a foraging-based approach, is well suited to routing problems since the pheromone system used in it inherently constructs discrete paths for graphs of networks. Predator-prey algorithms such as GWO show particular strength in adversarial security contexts, where the predator-prey dynamic models the attacker-defender relationship effectively. The bat algorithm and its enhanced variants achieve the lowest localisation errors due to their echolocation-inspired frequency tuning emulating the coarse-to-fine localisation procedure. Such patterns of alignment inform us that algorithm choice is driven by not only performance considerations but also the fundamental nature of the underlying optimisation problem.

Addressing Research Question 2 (What modifications are required to adapt SI algorithms to sensor network constraints?), hybridisation is found to be a robust good practice in general, and the combinations of exploration-based (GA, ABC) and exploitation-based (PSO, ACO) algorithms give rise to super-linear synergy effects from 18 to 31% for all considered applications. This result reinforces the theoretical understanding that sensor network optimisation is based on irregular fitness functions with many local maxima—exploration is sustained for refining exploitation to achieve the best performance in the end. The very effective recent hybrids are based on either quantum-inspired components (QSI-PSO) or federated learning (FSI-ABC), so it seems that hybridisation with new paradigms will continue to bring improvement. Additionally, energy-aware fitness functions, distributed and decentralised operation, dynamic parameter adaptation, and multi-objective optimisation frameworks have proven essential for adapting SI algorithms to the resource-constrained, dynamic nature of sensor networks.

Addressing Research Question 3 (What are the quantitative performance improvements of recent algorithms compared to classical approaches?), Quantum-Inspired SI achieves $O(1/t^2)$ convergence—35-45% faster than classical $O(1/t)$ algorithms—by leveraging superposition for parallel exploration. Federated Swarm Intelligence reduces communication overhead by 50-70% while preserving privacy with minimal performance trade-off (2% coverage reduction for 2.5× privacy gain). These quantitative improvements confirm that recent algorithms (2022-2026) achieve 30-80% relative improvements over classical approaches, with specific gains including a 36-47% improvement in deployment coverage, a 51-82% improvement in network lifetime extension, and a 57-86% reduction in localisation error.

Despite these advances, several limitations characterise current research and must be acknowledged. A staggering 92% of the surveys are based on simulations alone, with only 8% on physical testbed validation. This disconnect leads to scepticism about applicability in the real world—simulations are unable to model hardware imperfections, radio interference, or the chaotic environmental dynamics that are prominent in real sensor network installations. Furthermore, most of the experiments were conducted on networks of 100-500 nodes, with approximately 12% on 1000+ nodes, while scalability to massive IoT deployments is still unknown. 65% of recent articles lack complete reporting on parameter settings, and hence reproduction is impossible: for quantum-inspired algorithms, critical parameters such as qubit count and rotation angles are often totally missing. Network lifetime investigations often ran 500-2000 rounds (hours to days) of simulations, at odds with months to years of required operation for actual deployments; long-term dynamical effects—battery depletion, environmental alterations, and node failure cascades—are scarcely simulated. These limitations highlight the need for more rigorous experimental validation, standardised reporting practices, and longer-term deployment studies.

For practitioners, these results correspond to tangible advice. For real applications, the QSI algorithm can reach full coverage (98% of nodes) if enough computing power is available, while EBWO achieves balanced coverage (95% of nodes) with much faster convergence. For routing, the QSI method enjoys the best lifetime improvement (51%), and the MPDO approach has the second-best performance (42%) with excellent scalability. For localisation, QSI yields the most accurate result (1.8% error), with EBWO again standing as a good option for privacy-preserving applications. From a security standpoint, the highest detection rate (98.2%) is attained by QSI-IDS, while FSI-IDS is considered the best option in case of data privacy. Practical considerations for implementation are resource limitations—classical algorithms are still more suited for nodes with limited memory (e.g., IoT devices)—network size—distributed schemes are indispensable beyond 5,000 nodes—and power budget—GSO enhances sustainability for energy-harvesting sensors.

6. CONCLUSION

This paper has presented a comprehensive, systematic review with meta-analysis of swarm intelligence algorithms applied to network sensor systems, with a specific focus on recent developments from 2022 to 2026, and directly addresses the three research questions stated in the abstract. Regarding RQ1 (How do different SI algorithm families perform across applications?), we developed a unified classification framework categorising over 50 SI algorithms—including 20 recent algorithms (2022–2026)—by inspiration source, operational mechanism, and applicability. This taxonomy reveals the accelerating diversification of nature-inspired algorithms and provides a roadmap for algorithm selection. Our meta-analysis of 85 peer-reviewed studies demonstrates that flocking algorithms excel at continuous deployment problems (92-98% coverage), foraging algorithms dominate discrete routing problems (28-51% lifetime extension), and predator-prey algorithms show strength in adversarial security contexts (94-98% detection rate). Concerning RQ2 (What changes need to be made to SI algorithms to suit sensor limitations?), our analysis shows that hybrid solutions produce super-linear gains (18-31% improvement) when the exploration-orientated and exploitation-orientated modules are united. Quantum-inspired SI attains $O(1/t^2)$ convergence—30-40% faster than traditional $O(1/t)$ algorithms—through superposition, which facilitates parallel exploration. Federated Swarm Intelligence (FSI), while preserving the privacy and having very good performance with small degradation (2% coverage reduction for 2.5× gain in privacy), reduces the communication overhead by 50-70%. These adaptations — energy-aware fitness, decentralised operation, dynamic parameter adaptation, and hybridisation — are necessary for making SI algorithms workable under sensor network limitations. For RQ3 (How much do recent algorithms improve quantitatively on performance?), it is clear that many recent SI algorithms (from 2022 to 2026) significantly outperform classical ones. For execution, QSI attains 98% coverage in 78 iterations in case of (vs. PSO: 92% in 148 iterations) — a 6.5% absolute advancement amounting to a 75% gap reduction. For routing, QSI extends network lifetime by 51% (vs. ACO: 28%)—an 82% relative improvement. For localisation, QSI reduces error to 1.8% of communication range (vs BA: 4.2%)—a 57% error reduction. For security, QSI-IDS achieves 98.2% detection rate with 1.4% false positives—exceeding classical approaches by 4-5%.

The convergence of quantum computing, federated learning, and sustainability considerations defines the frontier of network sensor optimisation. As sensor systems scale to massive IoT and integrate with 6G networks, quantum-inspired and federated SI algorithms will play an increasingly critical role in enabling autonomous, resilient, privacy-preserving, and sustainable networked sensing. Nonetheless, the limitations observed in this review, namely the predominance of simulation-only validation (92%); the lack of scalability testing (only 12% test on 1000+ nodes); as well as incomplete parameter reporting (65%), need to be addressed by means of concrete future research directions. Therefore, we call for the research community to focus on physical testbed experiments with platforms like FIT IoT-LAB, Indriya, and FlockLab to substantiate simulation results and close the gap between theoretical performance and practical applicability. Second, systematic studies at the 10,000-100,000 node scale are urgently needed, as quantum-inspired and federated variants show particular promise for massive IoT deployments but remain unproven at such scales. Third, a unified benchmark suite should be established with standardised deployment terrains, routing topologies, localisation noise models, and security attack vectors, accompanied by documented scenario configurations to enable fair comparison across studies. Fourth, the theoretical foundations require development of convergence guarantees for QSI under dynamic topologies, privacy-utility trade-off bounds for FSI, and complexity analysis for quantum-classical hybrid algorithms. Fifth, open-source implementations of recent algorithms (EBWO, MPDO, QSI, FSI, and GSO) should be made available to facilitate reproduction, comparative analysis, and practical adoption. Sixth, it is necessary in future work to study the combination of SI with digital twins for real-time optimisation of DSNs to allow for predictive maintenance and adaptive reconfiguration driven by real-time network conditions. Seventhly, work on sustainable SI should develop carbon-aware fitness functions that explicitly model the carbon emissions of network operations, including energy source mix (grid vs. renewable) and transmission efficiency, in response to escalating environmental citations. By following these leads, the community can move the field from descriptive surveys to prescriptive frameworks that inform the design of future-end distributed sensing systems that are more autonomous, resilient, and sustainable.

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