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SWARM INTELLIGENCE IN INTERNET OF THINGS ENVIRONMENTS: A SCOPING REVIEW

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Abstract:

The rapid growth of the Internet of Things (IoT) has created significant challenges related to energy consumption, routing efficiency, resource allocation, communication reliability, and cybersecurity. Swarm Intelligence (SI) techniques have increasingly been adopted due to their adaptive and distributed optimization capabilities to address these issues. This study aimed to identify the SI techniques applied in IoT environments and to examine their major application domains and optimisation objectives. This scoping review is based on the six-stage framework proposed by Arksey and O'Malley. Scopus and Web of Science (WOS) are two databases used to find relevant studies based on the topic and published between 2020 and 2026. 19 journal articles were selected and analyzed using thematic and comparative approaches after applying the screening and eligibility criteria. The findings found that SI techniques have been widely adopted in a variety of IoT applications, including in cybersecurity, WSNs, fog computing, IIoT, smart cities, and intelligent transportation systems. Frequently applied SI techniques included PSO, ACO, ABC, SSA, CSA, ACS, FMGWO, and several hybrid optimisation frameworks. These approaches were found to improve energy efficiency, routing performance, resource allocation, QoS, communication reliability, intrusion detection, and network lifetime. The review also identified an increasing trend towards hybrid SI approaches that integrate swarm-based optimisation with deep learning, federated learning, and evolutionary optimization techniques. To conclude, this review demonstrates the significant contribution of swarm intelligence to IoT environment. Although there are some challenges that remain unresolved. In the future, research should focus on addressing these limitations to improve the adaptability and effectiveness of optimization strategies in IoT systems.

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Keyword:

Internet of Things (IoT), IoT Optimization, Resource Allocation, Smart Cities, Swarm Intelligence (SI)

Introduction

The Internet of Things (IoT) has become an important technology that connects physical devices, sensors, and communication networks to enable data collection and information exchange. The application of IoT technology is increasingly being included in smart healthcare, industrial automation, transportation systems, environmental monitoring, and smart city applications. As a result, the rapid growth of connected devices has increased the volume of generated data, creating greater demands for efficient communication, secure data processing, and effective resource management. However, there are several challenges related to scalability, energy consumption, routing efficiency, computational limitations, security, and data privacy that persist in IoT environments. Additionally, limited computational capacity and energy resources are common to most IoT devices. This creates difficulties in network optimization and communication management in large-scale, dynamic environments. At the same time, concerns about cybersecurity, data protection, and autonomous network management have increased as the number of interconnected devices grows. With the emergence of technologies like blockchain, security and privacy protection are getting wider, these technologies additionally result in increased resource consumption and processing overhead.

Notably, due to their adaptable, distributed, and intelligent optimization capabilities inspired by natural collective behaviour, academics have been investigating Swarm Intelligence (SI) techniques continually. Accordingly, a number of IoT optimization issues, including routing, energy management, clustering, resource allocation, task scheduling, and security enhancement, have been addressed by using SI techniques. However, recent studies in a variety of technological implementations and application sectors are still scattered and dispersed. Thus, the purpose of this scoping study is to identify SI approaches used in IoT systems and analyze the optimization goals and primary application areas of these techniques.

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Energy Efficiency and Network Lifetime

Energy efficiency and network lifetime remain important issues in IoT scenarios for Wireless Sensor Networks (WSNs). Moreover, IoT applications have risen in sectors including smart healthcare, environmental monitoring, industrial automation, and smart cities. According to Xu et al. (2024) and Cinar, (2023), energy efficiency, network topology, communication delay, and network lifetime were all identified to be improved by algorithms. To improve energy efficiency and network performance in IoT environments, several SI algorithms, including Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Bee Colony Optimization (BCO), Artificial Bee Colony (ABC), Salp Swarm Algorithm (SSA), and Tree-Seed Algorithm (TSA), have been applied. Previous studies also reported that ABC and TSA achieved favourable results in transmission power optimisation for IoT-based WSNs (Cinar, 2023). In addition, SI techniques have been widely employed for routing optimisation and cluster head selection, contributing to better energy balancing, network stability, and communication efficiency (Raslan et al., 2020; Bhardwaj et al., 2025). These observations suggest that adaptive and multi-objective SI approaches continue to attract attention as potential solutions for managing the increasing complexity of large-scale IoT networks (Bhardwaj et al., 2025).

Materials and Method

This study approach is to systematically examine the available literature and identify key themes, trends, and areas for future research. Other than that, it strengthens the proposal of the research issues by drawing on past evidence and enriches knowledge by exploring uncharted areas in the most recent research. Specifically, it helps the researcher understand the significance of the idea from multiple viewpoints, enabling further discussion of the concept. In contrast to a systematic literature review, which necessitates the application of a set of methodological procedures, a scoping review can employ a range of techniques. As such, this research article employs the six-step methodology developed by Arksey & O'Malley, (2005) as explained in the section below:

Step (1): Identifying the research question to be carried out. This research focuses on the application of SI techniques in IoT environments. The Research Questions (RQs) were formulated to support a systematic and comprehensive exploration of the existing literature on swarm intelligence approaches, their application areas, implementation strategies, challenges, and research trends in IoT systems. The research questions for this review are: Which swarm intelligence (SI) algorithms are commonly used in IoT environments? Which IoT application domains have adopted SI techniques?

Step (2): Identify past research that is relevant to the objectives of the scoping review. Several relevant search phrases were used to ensure a comprehensive review of the available literature. Web of Science (WoS) and Scopus are two databases used for this review. Based on the selected main themes and search keywords, studies related to SI approaches in IoT environments were identified, as illustrated in Figure 1.

Step (3): Select the articles that are suitable for analysis. Specific inclusion and exclusion criteria were established for the publications considered in this scoping review. First, only publications related to IoT environments and swarm intelligence were included. Second, only research articles were eligible for inclusion in the scoping review, whereas conference

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proceedings, book chapters, review papers, and books were excluded. Third, only English-language publications from 2020 to 2026 were included, as illustrated in Figure 1. The database search was conducted in May 2026. Therefore, the review included studies published between January 2020 and May 2026.

Step (4): Charting the data to be presented. Mendeley and Microsoft Excel were used to organize and present the collected data graphically and to support the thematic and comparative analysis. To facilitate interpretation of the findings and address the RQs, a comprehensive table was developed that includes the authors' names, publication years, swarm intelligence techniques used, application domains, performance metrics, and major research gaps.

Step (5): Collating, summarizing, and reporting the data. To develop a clear and comprehensive discussion of the application of SI techniques in IoT environments, the findings were reorganized into identified topics, major themes, and sub-themes. Consequently, each article was classified and discussed based on the themes and sub-themes derived from the thematic and comparative analysis (Table 1). Figures 3 and 4 present the characteristics of the published scientific literature.

Step (6): Discussion of the results. The research findings are discussed in light of the objectives of this study. Since this topic remains relatively new in IoT environments, the limitations of existing studies and general recommendations for future research related to SI optimization techniques are also presented.

Findings

A total of 1,151 records were initially identified through database searching, comprising 738 records from Scopus and 413 records from the WoS. The search focused on publications published between 2020 and 2026 within the subject areas of Mathematics, Computer Science, and Artificial Intelligence (AI). Records that were systematic reviews, review articles, meta-analyses, meta-syntheses, books, book chapters, non-English publications, and studies published before 2020 were excluded. Following the application of these criteria, 363 records were removed, leaving 788 records for the screening stage. The titles and abstracts of the remaining records were screened to determine their relevance to swarm intelligence optimisation in IoT environments. No duplicate records were identified. Thirty-two articles were assessed for full-text eligibility. A further 13 articles were excluded because they were not based on empirical data, were conference proceedings, focused on hard sciences, or did not specifically address swarm intelligence optimisation in IoT applications. Consequently, 19 studies satisfied all inclusion criteria and were included in the final review, as illustrated in Figure 1.

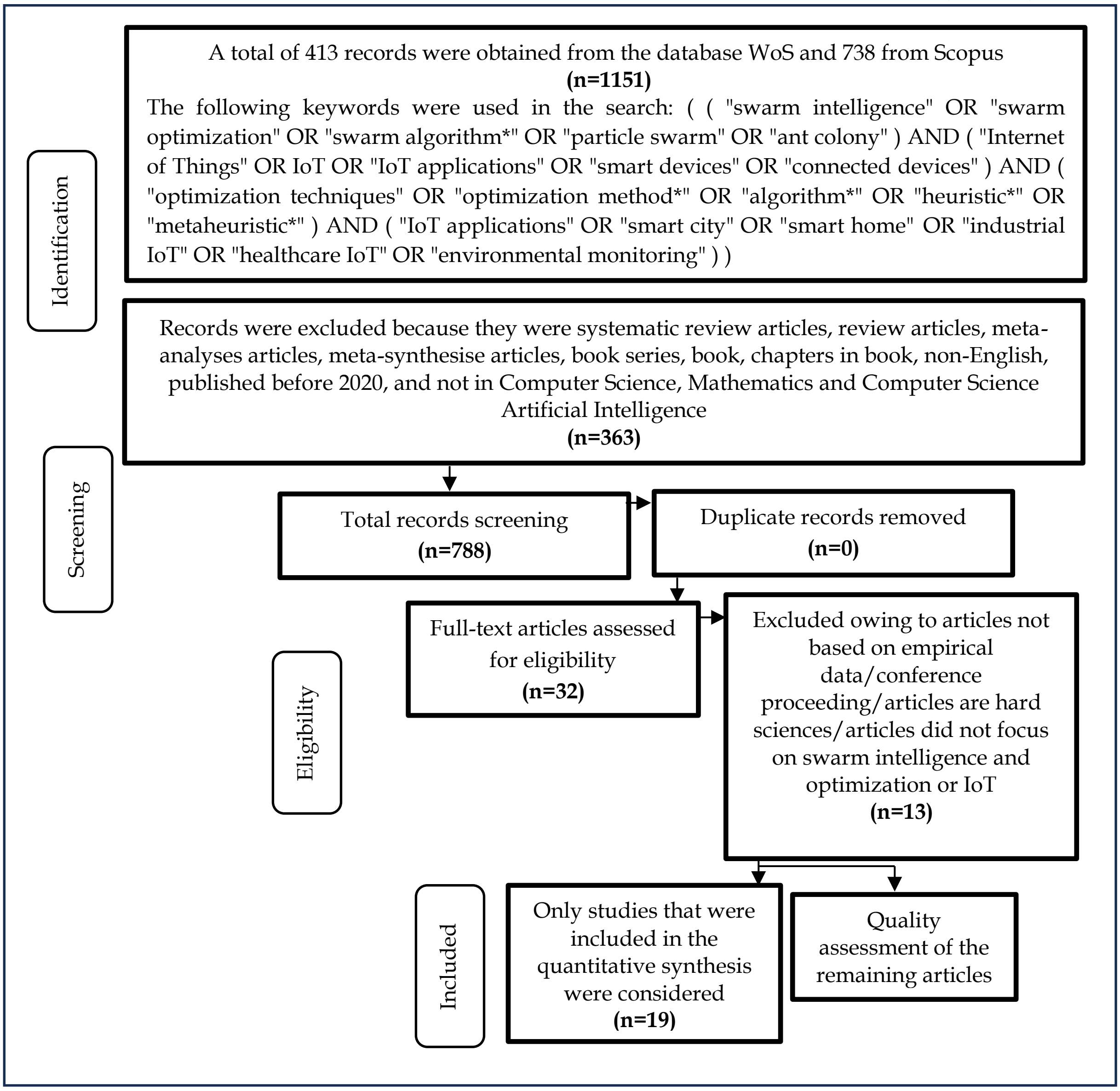

Figure 1: Flow Diagram of Research Selection Process Using Preferred Reporting Items for Systematic Reviews (PRISMA)
Source: Adapted from a study by (Moher et al., 2009)

Main Findings

The 19 studies that were a component of this scoping review are summarized in Table 1. Analysis of the selected studies indicates that research on SI in IoT has mainly focused on energy management, resource allocation, security enhancement, and smart city applications. These themes appeared repeatedly across the reviewed literature, suggesting their importance in current IoT optimization research. According to Mohammed et al. (2025) and S. Kumar et al. (2020), SI techniques have become crucial for solving optimization problems in dynamic IoT contexts. Also, fog computing and resource management have become significant SI application areas. Moreover, several studies (Bhaskaran et al., 2022; Anu & Singhrova, 2023; P. J. Kumar & Neduncheliyan, 2024; Farhadpour et al., 2026; Gad et al., 2024) demonstrate the success rate of SI approaches in enhancing resource allocation, task scheduling, Quality of

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Service (QoS), execution efficiency, and cost management in IoT and fog computing environments. As well, these methods have been used more frequently in IoT security frameworks, improving intrusion detection capabilities, reducing computing cost, while improving privacy protection (Arvaneh et al., 2024; El-Fouly et al., 2023; Alahmari & Alkharashi, 2025). Another prominent area of application was smart cities and intelligent monitoring systems. Another important point is to improve smart transportation monitoring, driver behaviour detection, communication reliability, and real-time decision-making capabilities reported by Dhuheir et al. (2025) and Siddiqa et al. (2025) approaches. Besides, El-Fouly et al. (2023) and Liu et al. (2025), environment-aware routing and advanced optimisation frameworks such as Fuzzy Modified Grey Wolf Optimizer (FMGWO) improved PDR, network coverage, resource efficiency, and communication performance in IoT-based WSNs. Overall, these findings show the growing role of SI in supporting IoT applications.

Table 1: Charting the Data

Publication / Location	Swarm Intelligence Technique	Findings	Sub-Theme	Theme
(Mohammed et al., 2025)	PSO, ACO, BCO	Improved energy efficiency, optimized topology, reduced energy consumption, and prolonged network lifetime.	Energy Management	Energy Efficiency and Network Lifetime
(S. Kumar et al., 2020)	PSO, ABC, SSA, TSA	Optimized transmission power, reduced energy consumption, and extended network lifetime.	Transmission Power Optimization	
(J et al., 2024)	Cluster Head Optimization	Improved cluster head selection, energy efficiency, and network lifetime.	Cluster Head Optimization	
(Prabhakar & Shaik, 2026)	Swarm Intelligence Routing Optimization	Enhanced routing efficiency, communication performance, and energy savings.	Routing and Energy Optimization	
(Chen et al., 2025)	Swarm Intelligence Clustering	Improved communication efficiency and balanced energy consumption.	Clustering Optimization	

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(Arvaneh et al., 2024)	Swarm Intelligence Intrusion Detection Framework	Improved intrusion detection and reduced computational overhead.	Security Optimization	IoT Security and Resource Optimization
(Bhaskaran et al., 2022)	Evolutionary Optimization / Metaheuristic Optimization	Optimized task placement, reduced cost, and improved QoS.	Resource Allocation	Resource Management and Fog Computing
(Anu & Singhrova, 2023)	Levy Flight Firefly Algorithm (LFFA)	Reduced execution time, energy consumption, and processing cost.	Fog Resource Optimization	
(P. J. Kumar & Neduncheliyan, 2024)	Swarm Intelligence Resource Allocation Model	Improved QoS and resource utilization.	QoS Optimization	
(Mohamed et al., 2025)	Metaheuristic Swarm Intelligence Algorithms	Enhanced resource allocation, scheduling, and QoS.	Resource Scheduling Optimization	
(Farhadpour et al., 2026)	Differential Evolution Genetic Algorithm (DE-GA)	Optimized resource allocation, cost, and makespan.	Multi-objective Optimization	Resource Management and Optimization
(Elfouly et al., 2021)	Hybrid Swarm Intelligence Framework	Improved intrusion detection and reduced false alarms.	Security Enhancement	IoT Security and Privacy
(Alahmari & Alkharashi, 2025)	Chameleon Swarm Algorithm (CSA) with Federated Learning	Enhanced intrusion detection, privacy, and scalability.	Privacy-Aware Intrusion Detection	
(Dhuheir et al., 2025)	Swarm-based intelligent optimization	Enhanced intelligent monitoring and real-time decision-making.	Smart Monitoring Optimization	Smart City Applications
(Siddiqa et al., 2025)	Ant Colony System (ACS)-optimized Deep Convolutional Neural	Improved driver detection and real-time monitoring.	Smart Transportation Optimization	Smart City and Intelligent Monitoring

	Networks (CNNs)			
(Gad et al., 2024)	Opposition-based Simulated Annealing Particle Swarm Optimizer (OSAPSO)	Reduced power consumption, cost, and execution time; improved QoS.	Cloud Task Scheduling Optimization	IIoT and Resource Optimization
(Yang et al., 2024)	Swarm-based optimization framework	Optimized resource allocation and communication performance.	Resource Allocation Optimization	Resource Management and Energy Optimization
(Liu et al., 2025)	FMGWO swarm intelligence framework	Enhanced coverage and resource efficiency.	Coverage Optimization	Energy Efficiency and Network Optimization
(El-Fouly et al., 2023)	Swarm Intelligence-based Environment-aware Routing Algorithm	Improved PDR, reduced delay, balanced energy use, and prolonged network lifetime.	Energy-Efficient Routing	Smart City and Intelligent Communication

Research Question Result

Research Question 1: What Swarm Intelligence Techniques Have Been Applied in Internet of Things (IoT) Environments?

The reviewed studies identified several SI techniques applied in IoT environments, as summarised in Table 2. These techniques included the algorithms of PSO, ACO, ABC, SSA, Ant Colony System (ACS), Crow Search Algorithm (CSA), FMGWO, and various hybrid SI frameworks. The identified techniques were applied across a range of domains, including WSNs, fog computing, Industrial Internet of Things (IIoT), cybersecurity, and smart transportation systems. However, there were several studies that also integrated SI with deep learning, federated learning, and evolutionary optimisation approaches to improve system performance, resource allocation, and decision-making in complex IoT environments.

Table 2: RQ1 Table Results

Author	Year	Swarm Intelligence Technique
(Mohammed et al., 2025)	2025	PSO, ACO, BCO
(S. Kumar et al., 2020)	2020	PSO, ABC, SSA, TSA
(J et al., 2024)	2024	Cluster Head Optimization
(Prabhakar & Shaik, 2026)	2026	Swarm Intelligence Routing Optimization
(Chen et al., 2025)	2025	Swarm Intelligence Clustering
(Arvaneh et al., 2024)	2024	Swarm Intelligence Intrusion Detection Framework

(Bhaskaran et al., 2022)	2022	Evolutionary Optimization/Metaheuristic Optimization
(Anu & Singhrova, 2023)	2023	LFFA
(P. J. Kumar & Neduncheliyan, 2024)	2024	Modified Shark Smell Optimization Algorithm
(Mohamed et al., 2025)	2025	Metaheuristic Swarm Intelligence Algorithms
(Farhadpour et al., 2026)	2026	DE-GA
(Elfouly et al., 2021)	2021	Hybrid Swarm Intelligence Framework
(Alahmari & Alkharashi, 2025)	2025	Crow Search Algorithm enhanced by Federated Learning
(Dhuheir et al., 2025)	2025	Swarm-based Intelligent Optimization
(Siddiqa et al., 2025)	2025	ACS-optimized Deep CNN
(Gad et al., 2024)	2024	OSAPSO
(Yang et al., 2024)	2024	Swarm-based Optimization Framework
(Liu et al., 2025)	2025	FMGWO Swarm Intelligence Framework
(El-Fouly et al., 2023)	2023	Swarm Intelligence-based Environment-aware Routing Algorithm

Research Question 2: Which IoT application domains have adopted SI techniques?

Table 3 outlines the key application areas of SI techniques within IoT systems. From the table, the overall trend indicates that SI techniques were commonly employed in WSNs, fog computing, smart cities, transportation systems, cybersecurity, and IIoT applications. In addition, the primary optimization objectives from these domains were to increase QoS, strengthen intrusion detection, extend network lifetime, optimize routing and resource allocation, and improve energy efficiency. For this reason, the results indicate that SI plays an important role in enhancing the efficiency and flexibility of IoT systems functioning in dynamic settings.

Table 3: RQ2 Table Results

Author	Application Areas	Optimization Objectives
(Mohammed et al., 2025)	WSNs, IoT energy management	Improve energy efficiency, optimize network topology, prolong network lifetime, and reduce node energy consumption
(S. Kumar et al., 2020)	IoT-based WSNs	Minimize transmission power consumption, maximize network lifetime, and optimize energy usage
(J et al., 2024)	IoT clustering and sensor communication	Improve cluster head selection, enhance energy awareness, and extend network lifetime
(Prabhakar & Shaik, 2026)	IoT-based WSN routing systems	Improve routing efficiency, reduce energy consumption, and prolong network lifetime
(Chen et al., 2025)	IoT sensor communication and clustering	Enhance communication efficiency, balance energy consumption, and improve scalability

(Arvaneh et al., 2024)	Smart city IoT security systems	Improve intrusion detection accuracy, reduce computational overhead, and optimize security performance
(Bhaskaran et al., 2022)	Fog computing and IoT resource management	Optimize task placement, reduce cost and make span, and improve QoS
(P.J. Kumar & Neduncheliyan, 2024)	Fog computing resource allocation	Reduce waiting time, execution time, processing cost, and energy consumption
(Anu & Singhroya, 2023)	Fog computing and IoT resource allocation	Maximize resource utilization and minimize processing time and operational cost
(Mohamed et al., 2025)	IoT and fog computing scheduling systems	Improve task scheduling efficiency, reduce processing delay, and enhance QoS
(Farhadpour et al., 2026)	Fog computing optimization environments	Improve Pareto-optimal resource allocation, optimize cost and make span trade-offs
(Elfouly et al., 2021)	IoT cybersecurity systems	Improve intrusion detection capability and reduce false detection rates
Alahmari & Alkharashi, 2025)	Federated learning-based IoT security systems	Enhance intrusion detection accuracy, preserve privacy, and improve scalability
(Dhuheir et al., 2025)	Smart city IoT monitoring systems	Improve intelligent monitoring and support real-time decision-making
(Siddiqa et al., 2025)	Smart transportation and intelligent monitoring	Improve driver detection accuracy and support real-time transportation monitoring
(Gad et al., 2024)	IIoT cloud scheduling systems	Reduce power consumption, operational cost, and execution time
(Yang et al., 2024)	Dynamic IoT resource management	Balance energy consumption, communication performance, and resource utilization
(Liu et al., 2025)	WSN coverage optimization	Improve sensing coverage, resource efficiency, and node deployment effectiveness
(El-Fouly et al., 2023)	Smart city WSN communication systems	Improve PDR, reduce delay, balance energy consumption, and prolong network lifetime

Review Findings and Gaps

Most studies have focused on nature-inspired optimization algorithms, such as ACO, PSO, GWO, and CSA, as well as several hybrid optimization approaches, to solve complex problems in IoT and WSN systems. The findings also reveal that SI algorithms can improve several key parameters, including energy consumption, latency, throughput, PDR, and network lifetime. For example, Mohammed et al. (2025) demonstrated that integrating Bluetooth Low-Energy (BLE) Mesh with ACO successfully reduced energy consumption by 35% and extended network lifetime by 40%. In addition, Liu et al. (2025) demonstrated that the FMGWO

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algorithm achieved network coverage of up to 98.63% with fewer sensor nodes. Other studies, such as Prabhakar & Shaik (2026) and Gad et al. (2024), also reported improvements in QoS, reduced processing cost, and more efficient task scheduling in cloud and fog computing environments. However, most of the reviewed studies were conducted in simulation environments, with limited validation in real-world IoT settings. Building on this, models were applied in dynamic, large-scale IoT environments, where they were reported to face challenges of computational complexity, high training requirements, and scalability. Moreover, for real-time applications, some optimization models require extensive parameter tuning, which may reduce their suitability. On a similar note, scalable SI models that can be practically implemented in real-time IoT systems remain relevant to develop lightweight, adaptive models. Table 4 presents a detailed comparison of the examined studies, including the research objectives, techniques, findings, strengths, and limitations. The combination of these results shows that SI techniques have shown an impressive amount of promise for enhancing cybersecurity, resource allocation, routing performance, and energy efficiency in IoT systems. Nonetheless, issues with scalability, computational complexity, parameter adjustment, and practical application continue to be significant research concerns.

Table 4: Detailed Review Findings and Research Gaps

Author (Year)	Scope / Research Objectives	Research Design	Samples	Findings	Strengths	Limitations / Gaps
(Mohammed et al., 2025)	To enhance energy efficiency, scalability, and network lifetime in WSNs using BLE Mesh and ACO	Simulation-based experimental study	WSNs with 1000 IoT sensor nodes	BLE-ACO reduced energy consumption by 35%, improved throughput by 25%, and extended network lifetime by 40%	Adaptive energy-aware routing, scalable BLE mesh integration, improved reliability and load balancing	Focused mainly on simulation environments with limited real-world implementation
(S. Kumar et al., 2020)	To compare ACO and K-Means clustering for job scheduling and energy optimization in IoT	Comparative and simulation-based study	IoT networks and scheduling environments	ACO and K-Means improved shortest path routing, reduced response time, and minimized energy consumption	Efficient QoS optimization and routing performance	High parameter tuning complexity and limited scalability analysis
(J et al., 2024)	To develop traffic-aware QoS routing in Software	Experimental QoS routing evaluation	SDIoT networks with QoS-sensitive IoT traffic	Proposed ACO routing improved delay, packet	Efficient QoS-aware routing with sustainable	Scalability and controller complexity

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	Defined IoT (SDIoT) using ACO			loss, jitter, and QoS flow management	network performance	issues remain unresolved
(Arvaneh et al., 2024)	To optimize resource allocation in fog computing for IoT applications using metaheuristic algorithms	MATLAB simulation-based comparative study	IoT applications in fog computing environments	The Cheetah algorithm outperformed the Gray Wolf and PSO-based methods in minimizing energy and processing time	Flexible optimization without strict constraints and strong optimization accuracy	Results validated mainly through simulations with limited practical deployment
(Bhaskaran et al., 2022)	To enhance IIoT security using blockchain-enabled lightweight cryptography and Chicken Swarm Optimization	Experimental cryptography and optimization study	IIoT image surveillance and industrial systems	BC-LWCIE improved image encryption security and secrecy in IIoT environments	Integration of blockchain with optimization-based cryptography	Focused primarily on image security applications rather than broader IIoT communication performance
(P. J. Kumar & Neduncheliyan, 2024)	To improve cybersecurity in IoT-based smart city infrastructure using ensemble deep learning and Shark Smell Optimization	Deep learning experimental framework	ToN-IoT smart city datasets	Achieved 99.78% attack detection accuracy with reduced latency and computational overhead	High intrusion detection accuracy and an adaptive fog-based framework	High computational complexity for large-scale IoT environments
(Farhadpour et al., 2026)	To optimize IoT application placement in fog computing using hybrid evolutionary optimization	Multi-objective evolutionary optimization study	IoT applications and heterogeneous fog nodes	The CEAP algorithm reduced cost, makespan, and deadline violations compared to existing methods	Strong Pareto-optimal multi-objective optimization and balanced search strategy	Complexity increases with heterogeneous large-scale fog environments
(Anu & Singhrova, 2023)	To improve resource allocation in fog computing using the LFFA	Simulation and comparative optimization study	Fog computing environments and IoT tasks	The proposed algorithm reduced execution time, waiting time, energy consumption,	Improved QoS and resource utilization using metaheuristic optimization	Limited by resource constraints and simulation-only evaluation

				and processing cost		
(Prabhakar & Shaik, 2026)	To optimize QoS parameters such as latency, throughput, energy consumption, and cost in Fog-IoT environments using a swarm optimization approach	Experimental and simulation-based optimization study	Fog-IoT applications with data volumes between 100-500 MB	HERSOA achieved better latency reduction, PDR, throughput, and energy efficiency compared to existing swarm algorithms	Integration of chaos theory with swarm intelligence improved global exploration and QoS optimization	Performance may degrade in highly dynamic and large-scale Fog-IoT environments
(Mohamed et al., 2025)	To reduce energy consumption and cost in fog-cloud IoT task scheduling using a hybrid metaheuristic algorithm	Simulation-based hybrid optimization study using iFogSim	IoT task scheduling and virtual machine environments in cloud-fog computing	EAEOSSA reduced energy consumption by 25.8% and cost by 21.15% while improving service time and productivity	Hybrid AEO and SSA improved the exploration and exploitation balance in optimization	High complexity in multitasking scheduling and dependence on simulation environments
(Chen et al., 2025)	To optimize blockchain computation task offloading in IoT using reinforcement learning-enabled swarm intelligence	Reinforcement learning and swarm intelligence optimization study	IoT blockchain devices with edge-cloud collaboration systems	RLSIOA achieved higher-quality offloading decisions with lower latency and improved device revenue	Combined reinforcement learning with swarm intelligence for adaptive dynamic optimization	Requires high computational training and complex parameter tuning in dynamic IoT systems
(Elfouly et al., 2021)	To optimize the deployment of heterogeneous WSNs considering coverage, mobility, and energy constraints	Integer Linear Programming (ILP) and swarm intelligence-based optimization	Large-scale heterogeneous WSNs with mobile and stationary nodes	The proposed algorithm improved coverage and network lifetime by more than 30% compared to	Considered node mobility, heterogeneity, coverage importance, and energy efficiency simultaneously	Deployment complexity increases significantly for large-scale and highly dynamic environments

				existing methods		
(Dhuheir et al., 2025)	To maximize energy harvesting and data rate in multi-UAV multi-RIS IoT systems using DRL and PSO	Deep reinforcement learning and PSO study	Multi-UAV, multi-RIS IoT communication systems	MDQPSO outperformed PPO-PSO, AC-PSO, and brute-force methods in energy harvesting and data transmission efficiency	Integrated DRL with PSO for adaptive UAV path planning and RIS optimization	High computational complexity and resource requirements for real-time deployment
(Alahmari & Alkharashi, 2025)	To enhance IoT intrusion detection and privacy preservation using federated learning and swarm intelligence optimization	Federated learning and AI-based intrusion detection study	IoT networks and healthcare IoT datasets	PEFLID-CSAAI achieved superior intrusion detection accuracy and privacy preservation compared to existing IDS models	Integrated SA-VAE, CSA, and OOA for feature selection and hyperparameter tuning	High computational complexity and scalability concerns in large IoT environments
(Siddiqa et al., 2025)	To detect distracted driver behavior in smart cities using IoT and ACS-optimized deep CNN models	IoT-based deep learning and feature optimization study	AUC distracted driver dataset and smart vehicle monitoring systems	Hybrid deep CNN and HOG features improved driver distraction detection accuracy up to 95.26%	Combined handcrafted and deep features with ACS optimization for robust classification	Increased training time and computational requirements for real-time deployment
(Gad et al., 2024)	To improve IIoT task scheduling in cloud computing using evolutionary swarm intelligence	Evolutionary swarm intelligence and cloud scheduling optimization study	IIoT heterogeneous task scheduling in cloud computing environments	OSAPSO improved power consumption, monetary cost, service makespan, and throughput compared to competing algorithms	Combined OBL, SA, evolutionary strategies, and PSO for enhanced exploration and convergence	Complexity increases for large-scale heterogeneous cloud environments
(Yang et al., 2024)	To design an IoT-based UAV patrol	UAV trajectory planning and	Urban patrol drones and	ICSA and DE-CSA improved	Integrated IoT, digital twins, and swarm	Focused mainly on simulation environments

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	platform for smart city governance using improved crow search optimization	swarm intelligence simulation study	smart city environments	trajectory planning accuracy and information collection efficiency	intelligence for urban patrol optimization	with limited real-world deployment validation
(Liu et al., 2025)	To optimize WSN coverage using a fusion multi-strategy gray wolf optimizer	Swarm intelligence and WSN coverage optimization study	WSNs in IoT and smart monitoring applications	FMGWO achieved up to 98.63% coverage with fewer sensor nodes and faster convergence	Integrated multiple optimization strategies to improve exploration, stability, and convergence	Increased algorithmic complexity and computational overhead in large-scale deployments
(El-Fouly et al., 2023)	To design an environment-aware, energy-efficient, and reliable routing protocol for real-time multi-sink WSNs in smart cities	ILP formulation and swarm intelligence heuristic routing study	Multi-sink WSNs for smart city applications	The proposed routing protocol improved PDR, network lifetime, delay, and reliability compared to SMRP and EERP	Considered environmental factors, real-time delivery, reliability, and energy balancing simultaneously	Higher computational energy consumption compared to existing routing algorithms

Technique vs Application Area in IoT Systems

The heatmap in Figure 2 illustrates the relationships between SI techniques and their application areas in IoT systems. The analysis reveals the distribution of SI techniques across different IoT application domains and highlights the most frequently adopted optimisation approaches. Accordingly, the results reveal that WSNs are the most common application field. A number of SI techniques, such as the algorithm of PSO, ACO, ABC, SSA, TSA, FMGWO, BCO, and hybrid swarm framework approaches, are being commonly used. As a result, WSN optimization is still an important field of study in IoT systems. Equally important, the analysis also reveals that fog computing is another important application area where techniques such as DE-GA, LFFA, SSA, Swarm Resource Allocation, and Swarm Routing Optimization were implemented. In fog computing environments, SI techniques were primarily used to improve task scheduling, resource allocation, latency reduction, and QoS performance. Different optimisation approaches, including DE-GA, LFFA, SSA, and swarm-based resource allocation models, were employed to address resource management challenges in dynamic IoT systems. In contrast, cybersecurity applications mainly focused on improving intrusion detection and strengthening system security through algorithms such as CSA and other metaheuristic optimisation techniques. For IIoT applications, evolutionary optimisation methods and OSAPSO were commonly adopted to enhance cloud scheduling efficiency and operational performance. The findings also indicate that SI techniques are increasingly being applied beyond traditional WSN and fog computing environments. Emerging application domains include Unmanned Aerial Vehicle (UAV)-assisted IoT, smart transportation systems, smart city

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networks, and IoT clustering applications. For example, Deep Reinforcement Learning (DRL) and PSO (DRL-PSO) were applied to optimise UAV communication systems, whereas ACS was utilised in intelligent transportation monitoring. These observations suggest that SI techniques can be adapted to different optimisation requirements, making them suitable for addressing communication, scalability, and resource management challenges in diverse IoT environments.

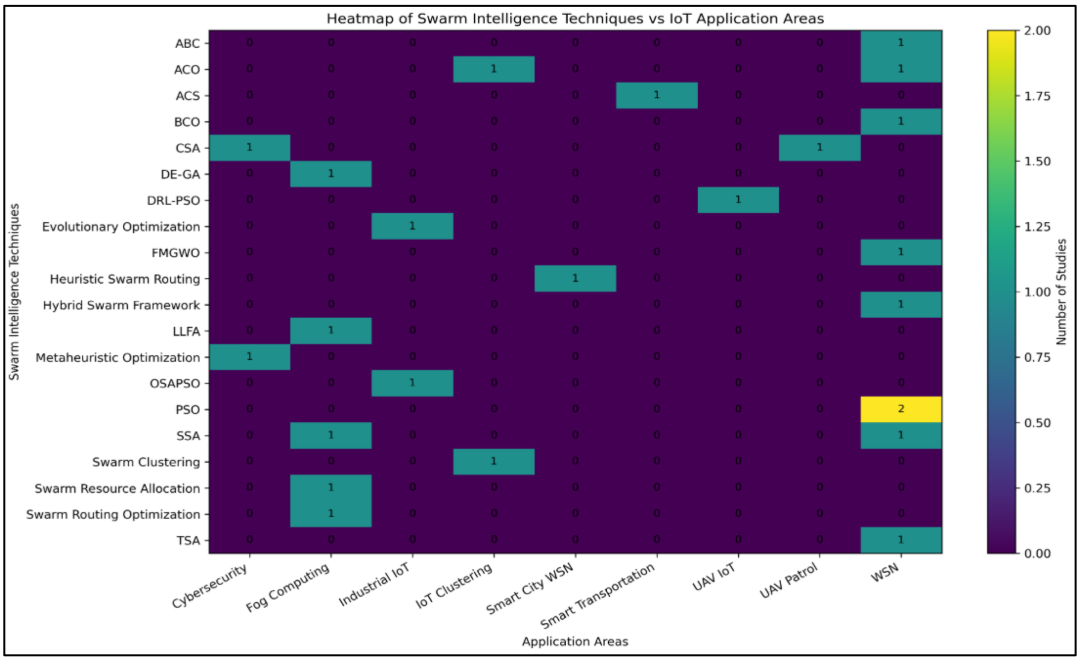

Figure 2: Heatmap of IoT Systems Technique vs. Application Area

Background of the Research Included In the Review

The studies included in this review were conducted across several countries, as presented in Figure 3. For countries like India, China, Egypt, Australia, Malaysia, Iran, Saudi Arabia, Qatar, Pakistan, and collaborative research comprising Egypt, Tunisia, and Saudi Arabia were among the nations where the evaluated studies were conducted. The Indian research population is very active when it comes to SI research in IoT contexts, as seen by the six publications that are the largest number of studies ever recorded in India. Additionally, China and Egypt carried out three studies, indicating that these nations are becoming more interested in SI optimization for IoT systems. In the meantime, Australia, Malaysia, Iran, Saudi Arabia, Qatar, and Pakistan each had one study.

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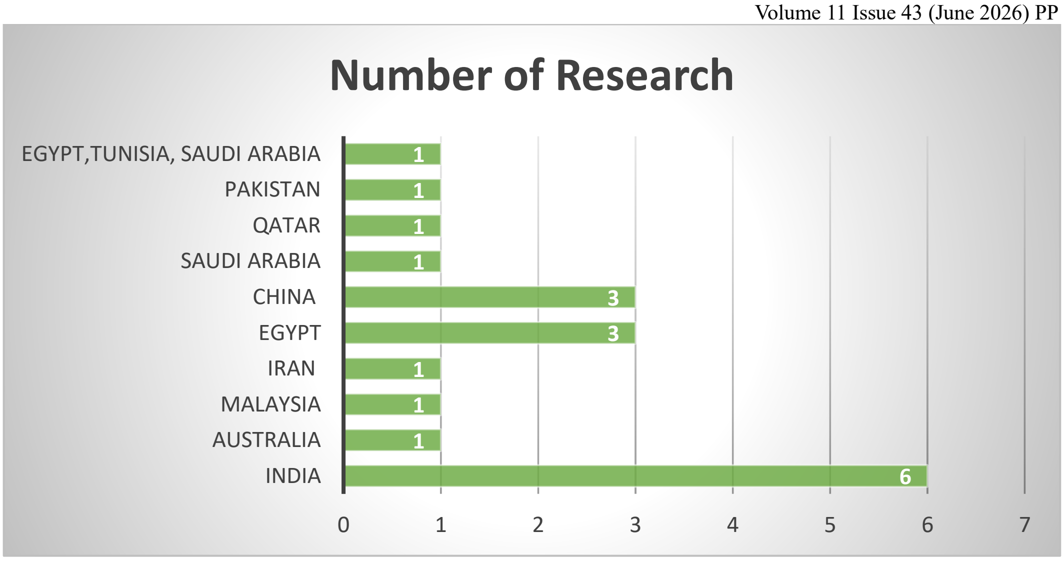

Figure 3: Number of Research Based on Countries

Year of Publications Database

The distribution of publications on swarm intelligence in IoT environments between 2020 and 2026 published that are indexed in the WoS and Scopus databases is shown in Figure 4. In fact, one pertinent publication was discovered in 2020. A more noticeable increase began after that, with two studies recorded in 2023 and one in each of 2021 and 2022. In 2024, there are five publications. Still, 2025 was the peak year with seven studies published. Solving optimization problems related to energy efficiency, routing, resource allocation, and intelligent communication systems is an interesting field for researchers seeking to apply SI techniques in IoT environments. In 2026, only two publications were identified. Essentially, the figure suggests that SI in IoT has emerged as an increasingly active area in recent years.

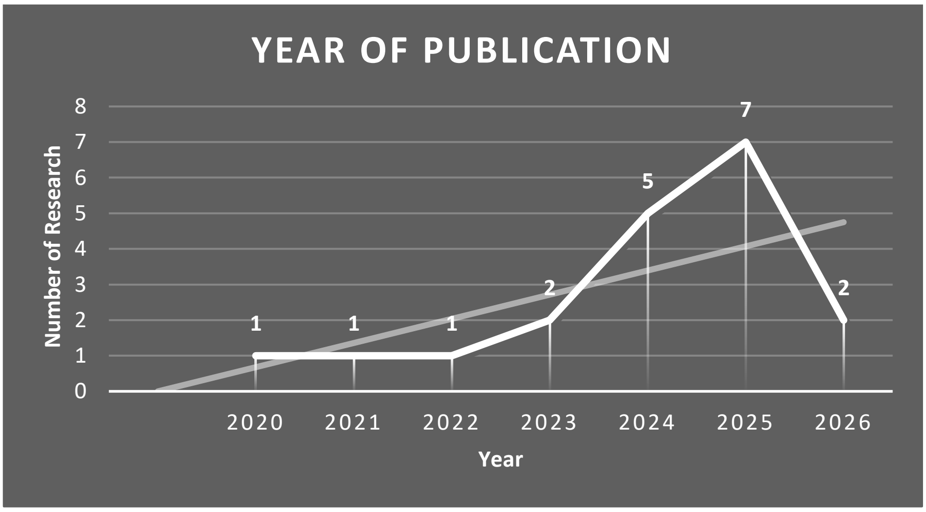

Figure 4: Year of Publication in WoS and Scopus Database

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Discussion

This scoping review presents a broad overview of how SI techniques are applied in different IoT environments. From Table 5, SI has shown considerable potential to enhance optimization processes in energy efficiency, routing performance, communication reliability, resource allocation, cybersecurity, and intelligent monitoring systems. The reviewed studies indicate that, in dynamic, large-scale IoT environments, these techniques are increasingly utilized due to their adaptive, distributed, and collaborative optimization characteristics, which are well-suited. SI techniques contribute to intelligent decision-making and autonomous optimization, thereby improving overall IoT system performance and operational sustainability (Mohammed et al., 2025; Mohamed et al., 2025; Liu et al., 2025).

The review found that WSNs continue to be the main application domain for SI approaches, such as ACO, PSO, SSA, FMGWO, and hybrid SI frameworks. Significantly, WSNs is one of the fields that frequently utilized to optimize energy consumption, sensing coverage, network lifetime, communication efficiency, and routing performance. Furthermore, to optimize resource allocation, reduce processing latency, and improve QoS, fog computing and cloud-fog IoT environments, techniques like LFFA, DE-GA, and other swarm optimization frameworks were widely used. According to S. Kumar et al. (2020), Anu & Singhrova (2023) and Farhadpour et al. (2026), these studies also imply that SI is important for solving difficult resource optimization problems in remote IoT infrastructures.

Although performance improvements were reported across the reviewed studies, several limitations remain. Particularly, PSO and ACO algorithms showed limits when used in extremely dynamic and expansive IoT environments. For these reasons, in order to efficiently seek out alternative solutions, these algorithms were frequently affected by rapid convergence. Following this, as the number of connected devices rises, routing-based optimization techniques typically need more computing work, which could have an impact on scalability and real-time performance. In order to overcome these difficulties, sophisticated and hybrid SI models were developed, although many of them still needed significant parameter adjustment and extra processing power. One recurring challenge identified across the studies was balancing optimisation performance with computational efficiency (S. Kumar et al., 2020; Gad et al., 2024; Farhadpour et al., 2026).

The reviewed studies indicate that optimisation requirements differ according to the characteristics of each IoT application domain. Since these algorithms were successful in meeting these optimization requirements, algorithms like PSO, ACO, and FMGWO became popular. Nevertheless, studies in IIoT and fog computing settings focused more on QoS, task scheduling, and resource allocation. Because hybrid optimization techniques like DE-GA and OSAPSO can handle several optimization targets at once, they typically yield better results in these situations. These findings indicate that for every IoT application, there isn't a single SI method that works well. Therefore, according to Farhadpour et al. (2026), Gad et al. (2024), Alahmari & Alkharashi (2025) and Liu et al. (2025), the optimization objectives, computing resources, and operational requirements of the IoT application under consideration should all be taken into consideration while selecting an SI algorithm.

This finding is consistent with previous studies, although positive improvements in IoT system performance were reported, several implementation-related limitations were also consistently identified. Despite the reported improvements in IoT system performance, the practical implementation of SI techniques remains limited. There are some limitations, as most studies rely on simulation-based evaluations, making it difficult to determine their effectiveness in real operational environments. Several challenges were repeatedly identified, including scalability constraints, computational complexity, parameter sensitivity, and interoperability issues. These factors may reduce the applicability of SI techniques in large-scale and highly dynamic IoT deployments. Consequently, further research is needed to validate existing optimisation models through practical testing and to develop more adaptive and scalable solutions for real-world IoT applications (Alahmari & Alkharashi, 2025; Dhuheir et al., 2025; Farhadpour et al., 2026).

Table 5: Mapping of Swarm Intelligence Applications in IoT Environments

Optimization Area	Swarm Intelligence Technique	Application Domain	References
Energy Optimization	ACO, PSO, SSA, FMGWO	WSNs, IoT Networks	Mohammed et al. (2025), S. Kumar et al. (2020), Mohamed et al. (2025) Liu et al. (2025)
Routing Optimization	ACO, Heuristic Swarm Routing, PSO	Smart City WSN, SDIoT, Multi-sink WSN	El-Fouly et al. (2023), Dhuheir et al. (2025)
Resource Allocation Optimization	LFFA, DE-GA, Metaheuristic Optimization, Swarm Optimization	Fog Computing, Cloud-Fog IoT, IIoT	Anu & Singhrova (2023), Farhadpour et al. (2026), Arvaneh et al. (2024) and Gad et al. (2024)
Security Optimization	CSA, Chicken Swarm Optimization, Shark Smell Optimization	IoT Cybersecurity, Smart City Security, IIoT Security	Alahmari & Alkharashi, (2025), Bhaskaran et al. (2022), P. J. Kumar & Neduncheliyan (2024)
Communication Optimization	PSO, DRL-PSO, FMGWO	UAV-assisted IoT, WSN Communication Systems	Dhuheir et al. (2025), Liu et al. (2025), Mohammed et al. (2025)
Intelligent Monitoring and Detection	ACS, CSA-based Optimization	Smart Transportation, UAV Patrol Systems	Siddiqa et al. (2025),Yang et al. (2024)
Clustering and Network Management	ACO, Swarm Clustering	IoT Clustering, SDIoT Networks	S. Kumar et al. (2020), Chen et al. (2025)

Table 6 compares the most frequently applied SI techniques in IoT environments. This table reports only the most common SI approaches. For each SI approach, there are advantages and disadvantages based on important optimization domains, such as processing needs, energy efficiency, routing performance, resource allocation, and security enhancement. Additionally, it also demonstrated the balance that frequently needs to be struck between optimization performance and implementation complexity. This comparison also offered insights into the viability of various approaches for particular IoT applications.

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Table 6: Comparative Study of SI Techniques in IoT Applications

Technique	Main Strengths	Limitations	Suitable IoT Applications
PSO	Low computational complexity.	Limited exploration in complex search spaces.	Wireless sensor networks with a focus on energy efficiency and clustering.
ACO	Efficient routing management in dynamic network environments	More significant in large networks	Routing, communication systems, SDIoT
SSA	Good exploration capability, balanced search process	Sensitive to parameter settings	Energy efficiency and resource allocation in IoT environments
FMGWO	Strong exploration and exploitation balance, avoids local optima	Increased algorithm complexity	Coverage optimisation, large-scale WSNs
CSA	Effective feature selection and security optimisation	Higher computational overhead	Intrusion detection, IoT security
Hybrid Models (DE-GA, OSAPSO)	Higher optimisation accuracy, multi-objective optimisation	Complex implementation and parameter tuning	Fog computing, IIoT, cloud scheduling

Moreover, Table 6 reveals that different SI techniques exhibit distinct strengths depending on the optimisation objectives and application requirements. In view of its simple structure, fast convergence, and relatively low computational requirements, the PSO algorithm is the most frequently applied SI technique. According to Mohammed et al., (2025), S. Kumar et al. (2020) and Gad et al. (2024),PSO-based approaches contributed to improvements in energy efficiency, resource utilisation, task scheduling, and QoS across various IoT and IIoT applications. Furthermore, PSO is a rational option for resource optimization and energy management, especially in IoT environments with limited computing and energy resources. However, the ACO algorithm performed better in communication management and routing optimization due to its capacity to dynamically find effective communication routes. Research from El-Fouly et al. (2023), J et al. (2024) and Mohammed et al. (2025) reveals thatACO-based optimization frameworks increased PDR, communication reliability, routing efficiency, and network stability. Overall, these results show that ACO is extremely useful for optimizing routing, particularly in WSNs, Software Defined IoT (SDIoT), and smart city communication systems, where adaptive and consistent routing is highly important.

Similarly, there are advanced SI algorithms such as SSA and FMGWO, which provide improved exploration and exploitation capabilities, enabling better optimisation performance in large-scale and complex IoT environments. According to Mohamed et al. (2025), the integration of SSA within hybrid optimisation models has improved energy efficiency and task scheduling performance in fog-cloud IoT systems. Similarly, Liu et al. (2025) demonstrated that FMGWO achieved superior coverage optimisation and resource efficiency in WSN deployments by reducing premature convergence and enhancing search stability. Nevertheless, these advanced techniques generally require higher computational resources and more sophisticated parameter tuning than conventional SI algorithms. The findings also indicate that

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CSA and hybrid SI frameworks are increasingly employed in security-oriented and multi-objective optimisation applications. As well as Alahmari & Alkharashi (2025), the studies demonstrated that CSA integrated with federated learning significantly improved intrusion detection accuracy, privacy preservation, and scalability in IoT security systems. Likewise, hybrid frameworks such as DE-GA and OSAPSO proposed by Farhadpour et al. (2026) and Gad et al. (2024) achieved superior optimisation performance in resource allocation, cloud scheduling, and cost minimisation by combining the strengths of multiple optimisation strategies. However, these hybrid approaches also introduce greater algorithmic complexity and computational overhead.

Overall, the suitability of a particular technique largely depended on the optimisation goals, application requirements, network conditions, and available computational resources. The findings also revealed an increasing interest in hybrid SI approaches, reflecting the need for more adaptive and multi-objective optimisation solutions to address the growing complexity of modern IoT systems (Farhadpour et al., 2026; Gad et al., 2024; Alahmari & Alkharashi, 2025).

Limitation and Recommendations

Several limitations should be acknowledged in this scoping review. First, this review focused only on publications indexed in the WoS and Scopus databases. Other databases, such as IEEE Xplore, SpringerLink, ScienceDirect, and ProQuest, may have limited the number of relevant studies on SI applications in IoT environments, although all are well known for providing high-quality and peer-reviewed publications. Some important studies and recent developments may not have been included in this review because of this selection. Furthermore, this review also selects only English-language publications published between 2020 and 2026. Hence, some studies published in languages other than English or outside the selected publication period were excluded from the analysis. Likewise, some earlier foundational studies and recent developments related to SI and IoT systems may have been overlooked as a result.

The primary focus of the reviewed studies is simulation-based experiments and specific IoT domains such as WSNs, fog computing, IIoT, and smart city environments. On the other hand, the major limitation is that the findings may not fully address the real-world challenges related to deployment complexity, heterogeneous network conditions, device interoperability, scalability, and operational constraints. Several limitations associated with SI techniques were identified across the reviewed studies. Common issues included premature convergence, computational complexity, parameter sensitivity, and higher resource requirements when operating in large-scale and dynamic IoT environments. These challenges may restrict the practical deployment of optimisation models, particularly in real-time applications. Furthermore, the rapid development of IoT technologies and optimisation methods means that new approaches continue to emerge, which may influence the relevance and completeness of the findings presented in this review.

Implications of the Study

This review examined the application of SI techniques across various IoT environments and identified the main optimisation areas addressed in the literature. The reviewed studies showed that SI algorithms have been widely applied to improve energy efficiency, routing performance, resource allocation, communication reliability, cybersecurity, and intelligent monitoring in domains such as WSNs, fog computing, IIoT, smart cities, UAV-assisted IoT, and intelligent transportation systems. The review also classified SI techniques according to their optimisation objectives and application domains, providing a clearer understanding of their roles in IoT systems. An increasing number of studies have explored hybrid SI approaches that combine swarm-based optimisation with deep learning, reinforcement learning, and federated learning to address more complex optimisation problems. In dynamic environments, several research gaps were also identified, particularly those related to scalability, computational requirements, parameter tuning, real-world implementation, and adaptability. These observations may assist future studies in developing SI-based solutions that are more efficient, scalable, and suitable for practical IoT applications.

Conclusion

The findings of this review indicate that SI techniques have become an important optimisation approach in IoT environments due to their ability to address complex and dynamic optimisation problems. The reviewed studies demonstrate the application of SI algorithms across a wide range of IoT domains, including WSNs, fog computing, IIoT, smart cities, and intelligent transportation systems. The review also highlights the most frequently adopted SI techniques, key optimisation objectives, and recent research trends reported in the literature. Collectively, these findings provide a clearer understanding of the current role of SI in supporting the performance and efficiency of IoT systems. Based on the results, the most often studied optimization areas in IoT research continue to be energy efficiency, route optimization, resource allocation, network longevity, communication performance, and security enhancement. This is because of the challenging optimization problems in WSNs, fog computing, IIoT, smart city systems, UAV-assisted IoT, and intelligent transportation environments, which were frequently solved using algorithms like PSO, ACO, SSA, CSA, and hybrid SI frameworks. More importantly, the need for more flexible and scalable optimization frameworks in dynamic IoT systems using a hybrid SI technique is also reflected and increased. However, for real-world settings, there are still difficulties, particularly with regard to computational complexity, scalability, parameter tuning, real-time adaptation, and the restricted application of swarm intelligence models. Alongside this, multi-objective swarm intelligence frameworks that better support large-scale, real-time IoT applications should receive greater attention in future studies. The review highlights the main application areas, optimisation objectives, and SI techniques that have been explored in IoT environments. It also identifies several research gaps and emerging areas that warrant further investigation. The findings may serve as a useful reference for researchers and practitioners seeking to develop intelligent and adaptive optimisation solutions for future IoT systems.

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