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Review

Recent Progress in Optimising Sustainable Energy Smart Grids Using Swarm Robotics: A Systematic Narrative Review

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Abstract

This systematic narrative review examines recent advances in the application of swarm robotics and swarm intelligence to smart grid systems in the context of renewable energy sources. Smart grids represent a transformative paradigm in power systems, integrating advanced communication, monitoring, and control technologies to enhance the reliability, performance, and sustainability of power distribution. Swarm robotics, drawing inspiration from the collective behaviour of social insects, enables the coordination of numerous autonomous agents to carry out complex tasks in a decentralised, scalable, and fault-tolerant manner. Over the past decade, swarm intelligence approaches—including Particle Swarm Optimisation, Ant Colony Optimisation, and consensus-based distributed control—have emerged as promising methods for addressing smart grid challenges such as decentralised energy management, fault detection, infrastructure monitoring, and maintenance. This review was conducted through a two-stage systematic search of three databases (Scopus, IEEE Xplore, and ACM Digital Library; Web of Science was not accessible during the search period and was therefore excluded), which identified 54 primary studies meeting the full-text inclusion criteria, supplemented by 11 additional records located through hand-search, for a final corpus of 65 references. For each application domain (monitoring and inspection, energy distribution optimisation, fault detection and resilience, and cybersecurity and communication), we summarise the methodologies employed, the reported performance outcomes, and the evidence level of the available studies. We also analyse the scalability limits of current swarm approaches, communication constraints relevant to grid deployment, and the integration of swarm systems with existing SCADA and EMS infrastructure. The review identifies a significant gap between laboratory demonstrations and utility-scale deployment, and outlines priority directions for future research.

Keywords: sustainable; renewable; energy sources; smart grids; swarm robotics; artificial intelligence; energy distribution; monitoring

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1. Introduction

The field of swarm robotics is inspired by the collaborative behaviour of social insects such as ants, termites, wasps, and bees [1]. Swarm systems envision groups of relatively simple robots cooperating to complete intricate tasks collectively—analogous to how an ant colony collaborates to locate food or construct its habitat. This principle is central to swarm robotics, where numerous independent robots, referred to as agents, interact locally with each other and their surroundings to accomplish shared objectives [2].

The focus of swarm robotics differs from traditional robotics in that it emphasises the importance of coordination and cooperation among a large number of simple robots rather than individual robot performance [3]. In a swarm, each robot typically adheres to simple rules based on local sensing and communication with nearby robots. These interactions give rise to emergent behaviours, leading to complex collective actions such as exploration, mapping, surveillance, and disaster response [4].

According to Şahin [5] there are five characteristics to describe the robots as swarm:

i. The swarm's robots need to be self-sufficient, with the ability to perceive and respond to their surroundings.
ii. There must be a large number of robots which cooperate in the swarm.
iii. Homogeneous of the robots. The swarm may have a variety of robot types, but there should not be an excessive number of these groups.
iv. Robots must be unable or ineffective with regard to the primary goal they must do; that is, they must work together to be successful or perform better.
v. Robots are limited to local sensing and communication. It guarantees distributed coordination, making scalability one of the system's properties.

According to Nedjah & Junior [6] the main features of Swarm Robotics has three main features:

- Robustness: Even in the event that certain components malfunction, the system must be able to complete the intended mission. The aggregate robustness of a distributed system with independent agents is its greatest advantage, even in the event that a few members of the system exhibit problems.
- Flexibility: The system must be adaptable/flexible. Put another way, despite having limited resources for observation and communication, they must fulfil a variety of roles and responsibilities.
- Scalability: The system must maintain its performance and coordination capability as the number of agents increases, without requiring centralised control or proportional increases in computational resources.

Swarm robotics finds applications in various domains, including agriculture for crop monitoring and harvesting, search and rescue operations in hazardous environments, manufacturing for coordinated assembly tasks, and renewable energy systems and smart grids for optimising energy distribution, monitoring, and maintenance. The potential scalability, robustness, and flexibility of swarm systems make them a promising approach for tackling complex real-world challenges where single-robot solutions may be insufficient. Overall, swarm robotics represents a paradigm shift in robotics, emphasising the power of collective intelligence and distributed control to achieve tasks that exceed the capabilities of individual robots.

A comprehensive review of the recent literature on this subject reveals several notable advances. Researchers have proposed the use of swarm robotics to monitor and maintain renewable energy infrastructure, such as wind turbines and solar panels, reducing the need for manual inspection and maintenance [7]. Swarm robots have also been explored for the dynamic optimisation of energy distribution, allowing real-time adjustments to demand and supply fluctuations, and thereby maximising the utilisation of renewable energy sources.

Furthermore, the integration of swarm robotics with advanced control and communication technologies, such as fuzzy logic controllers and wireless sensor networks, has enabled more intelligent and coordinated decision-making within the grid system. This

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has led to improvements in energy management, reducing costs and greenhouse gas emissions, while enhancing the overall reliability and resilience of the grid

The promising potential of swarm robotics in smart grid systems has been highlighted in several recent studies. These works have demonstrated the benefits of incorporating swarm robotics, including improved energy efficiency, increased renewable energy integration, and enhanced grid stability.

This paper is organised as follows: In Section 2, we analyse the smart grid in Renewable Energy. Section 3 analyzes swarm robotics in the field of smart grid, in Section 4 we discussed the gathered information and in Section 5 we present the conclusions.

2. Smart Grid and Renewable Energy

2.1. Search Methodology and Study Selection

This review followed a two-stage systematic search process. An initial database search was conducted in January 2025 across three databases: Scopus, IEEE Xplore, and ACM Digital Library. The search string combined terms from three concept clusters: (swarm robotics OR multi-agent) AND (smart grid OR microgrid OR power grid OR energy distribution OR renewable energy) AND (optimisation OR control OR monitoring OR maintenance OR fault detection). A supplementary search was conducted from January 2000 to June 2025 to capture relevant publications appearing after the initial search date.

As illustrated in Figure 1, the literature selection process followed a structured four-phase screening protocol consistent with PRISMA reporting guidelines. In the identification phase, systematic searches were conducted across three databases, Scopus (n = 294), IEEE Xplore (n = 265), and ACM Digital Library (n = 267), yielding a combined total of 826 records. Web of Science was not accessible during the search period and was therefore excluded from the search scope. A supplementary hand-search conducted in April–June 2025 identified a further 11 records not captured by the automated queries. Following the removal of 84 duplicate records, 742 unique entries advanced to the screening phase, in which title and abstract review resulted in the exclusion of 658 records whose subject matter did not simultaneously address swarm robotics or swarm intelligence and energy or grid systems. The remaining 84 records proceeded to the eligibility phase, where full-text assessment against the pre-defined inclusion criteria identified 30 articles for exclusion: 14 were non-peer-reviewed or published in venues of insufficient methodological standing; 12 described purely software-based multi-agent systems with no physically embodied robotic analog; and four provided insufficient methodological reporting to permit meaningful quality assessment. The resulting 54 full-text eligible studies, combined with the 11 supplementary records, constitute the final inclusion corpus of 65 references that forms the evidential basis of this review. The predominance of laboratory-scale evidence within this corpus—with 41 studies (63.1%) relying exclusively on controlled experimental or simulated settings—is itself a substantive finding, reflecting the current developmental stage of the field and indicating that utility-scale deployment of swarm robotics in operational smart grid environments remains an open research challenge rather than an established practice. It should be noted that this 65-reference corpus is distinct from the manuscript's full reference list: a further set of citations used elsewhere in the text (e.g., foundational algorithmic papers on particle swarm optimisation and consensus control, general smart grid or swarm robotics surveys used for background framing, and theoretical papers on distributed-systems fault models such as the Byzantine Generals problem and the Sybil attack) are cited for definitional or theoretical context rather than as primary studies identified through the systematic search process described above, and are not counted among the 65 primary studies. A quality assessment framework was applied to all included studies. Each study was evaluated on four criteria:

1. Relevance to swarm robotics or swarm intelligence applied to energy or grid contexts;
2. Methodological rigour (experimental validation vs. simulation vs. purely conceptual);
3. Publication venue quality (peer-reviewed journal or indexed conference proceedings);
4. Recency (studies prior to 2010 included only if foundational).

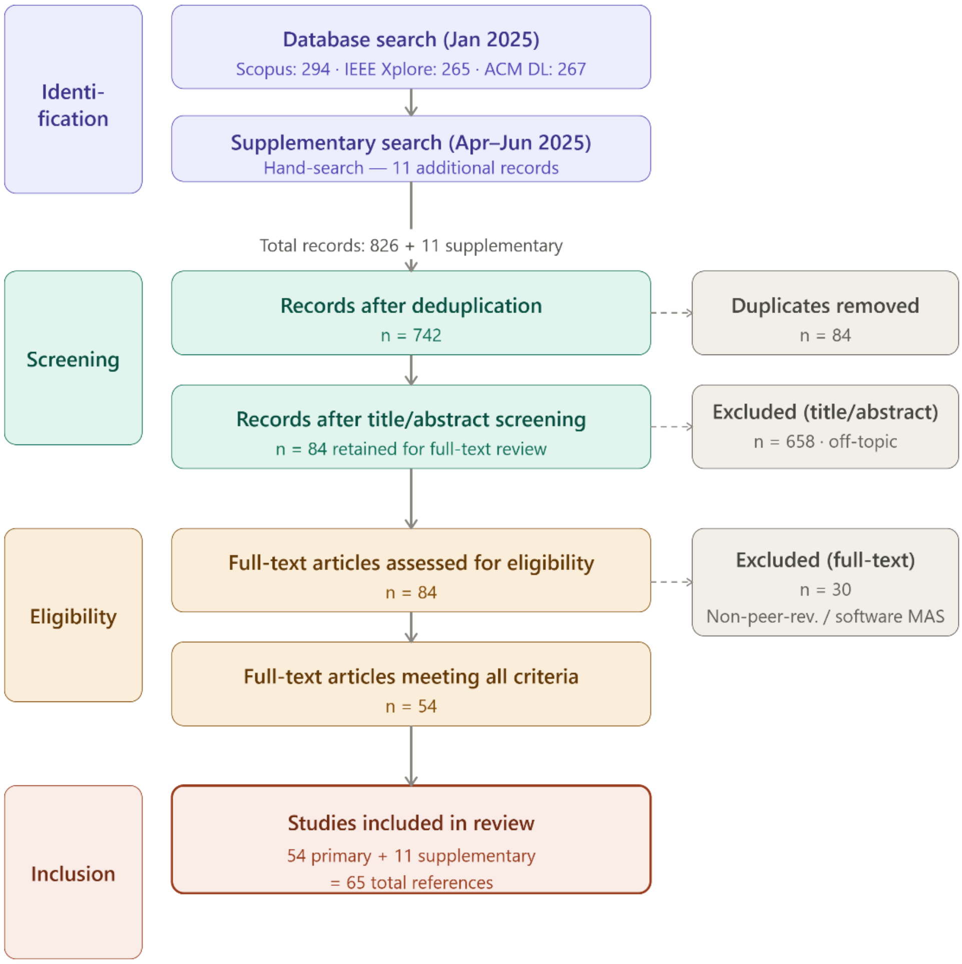

Figure 1. PRISMA-style flow diagram of the literature search and selection process.

Studies meeting all four criteria were classified as primary evidence; those meeting criteria 1, 3, and 4 but only partially criterion 2 were classified as secondary/contextual. Table 1 summarises the classification of all included studies by evidence level. The predominance of laboratory-level evidence is itself a key finding of this review, reported explicitly in the Section 4.

Table 1. Distribution and characterisation of reviewed studies by evidence level.

Evidence Level/ Deployment Stage	Characterisation and Scope	Number of Studies (n)	Percentage (%)
Laboratory demonstrations	Majority of reviewed studies	41	63.1%
Pilot-scale field trials	Includes drone-based photovoltaic panel inspection trials and multi-robot substation inspection trials	18	27.7%
Commercial/utility-scale deployment	Currently limited to single-robot or small-fleet systems rather than swarms in the strict sense	6	9.2%
Total	All included studies	65	100.0%

Table 2 cross-tabulates the selected literature ($N = 65$) by application domain and evidence level, providing an overview of the current technical maturity across different sectors. Monitoring and inspection emerges as the most extensively researched domain ($n = 32$), demonstrating the highest rate of progression from laboratory environments ($n = 18$) to pilot-scale field trials ($n = 12$) and utility-scale deployments ($n = 2$). Conversely, research in energy distribution optimisation ($n = 21$) and fault detection and resilience (n = 12) remains predominantly confined to laboratory-scale testing, with limited translation to commercial utility infrastructure. Notably, a significant research gap is identified within the cybersecurity and communication domain; no empirical or physical deployments were documented ($n = 0$), as the contemporary literature in this subfield remains strictly conceptual. Collectively, these findings underscore a broader trend in the state of the art: while the foundational groundwork is firmly established via laboratory demonstrations ($n = 41$), full utility-scale validation remains scarce ($n = 6$), highlighting the critical need for scaling up multi-robot and swarm architectures in real-world operational environments.

Table 2. Evidence level classification of reviewed studies by application domain.

Domain	Laboratory (*n*)	Pilot/Field (*n*)	Utility-Scale (*n*)
Monitoring and inspection	18	12	2
Energy distribution optimisation	14	4	3
Fault detection and resilience	9	2	1
Cybersecurity and communication	0	0	0 *(all conceptual)*
Total	41	18	6

The empirical efficacy of swarm intelligence across diverse smart grid application domains is robustly demonstrated by the quantitative metrics synthesised in Table 3. In terms of generation and localised energy asset management, decentralised optimisation approaches yield substantial economic and operational advantages; specifically, Jemaï [7] reported a 12–18% efficiency improvement in wind farm integration over conventional baselines, while Paul et al. [8] reported a 9.67% reduction in operational costs and a 13.23% reduction in carbon emissions using a quantum-inspired particle swarm optimisation (QPSO) framework for day-ahead microgrid scheduling. Jo et al. [9] demonstrated a measurable reduction in network overhead within smart metering frameworks compared to traditional centralised architectures. Finally, from a grid stability perspective, the distributed consensus-based voltage and frequency controller proposed by Alghamdi [10] reduced frequency deviation under sudden load disturbances from 0.45 Hz to 0.15 Hz (a 66% improvement) and cut post-fault voltage-recovery time from 2.5 s to 1.1 s in an isolated microgrid testbed. Collectively, these quantitative outcomes are encouraging, but they come almost entirely from simulation studies on small-scale or benchmark microgrids rather than from field deployments on utility-scale power systems; as discussed further in Section 4, translating these results into the reliability, bandwidth, and economic constraints of full-scale grid operation remains an open challenge.

Table 3. Quantitative performance metrics reported in reviewed studies by application area.

Study	Application	Metric	Reported Result
Jemaï [7]	Wind farm integration	Efficiency improvement	12–18% vs. baseline
Jo et al. [9]	Smart metering	Overhead reduction	Measurable vs. centralised

Paul et al. [8]	Microgrid energy management	Operational cost reduction	9.67% vs. DE baseline
Alghamdi [10]	Voltage/frequency control (FIDVR)	Post-fault voltage-recovery time	1.1 s (56% faster)

2.2. Taxonomy: Swarm Robotics vs. General Multi-Agent Systems

To clarify the scope of this review, Table 4 presents a taxonomy distinguishing swarm robotics from general multi-agent systems (MAS) along four dimensions. This distinction is important because the reviewed literature sometimes uses these terms interchangeably, whereas they reflect fundamentally different design philosophies with different implications for smart grid deployment.

Table 4 outlines a comparative taxonomy that distinguishes swarm robotics from general multi-agent systems (MAS) across four foundational dimensions, specifically contextualising their relevance to smart grid deployments. While general MAS architecture often accommodates heterogeneous agents and rely on global, hierarchical, or broadcast communication schemes, swarm robotics is characterised by agent homogeneity and localised, neighbour-to-neighbour communication topologies. Within smart grid frameworks, these distinctions are highly consequential: homogeneous swarms streamline the design of coordination protocols for monitoring fleets, whereas localised communication significantly reduces dependency on external telecommunication infrastructure, thereby eliminating single points of failure. Furthermore, the scalability design of swarm systems predicted on emergent coordination—ensures that performance is maintained or enhanced as the system size (n) scales, which is critical for geographically dispersed grid-scale infrastructure. Lastly, unlike MAS, which widely utilises virtual software agents, swarm robotics mandates physical embodiment (e.g., UAVs or ground robots), a necessary prerequisite for executing physical maintenance, inspection, and direct interactions with smart grid assets.

Table 4. Taxonomy distinguishing swarm robotics from general multi-agent systems (MAS) along four key dimensions relevant to smart grid deployment.

Dimension	Swarm Robotics	General MAS	Grid Relevance
Agent homogeneity	Typically homogeneous (identical agents)	May be heterogeneous	Homogeneous swarms simplify coordination protocol design for grid monitoring fleets
Communication topology	Local/neighbour-only; no global communication	May use global, hierarchical, or broadcast communication	Local communication reduces infrastructure dependency and single points of failure
Scalability design	Designed for large with emergent coordination; performance maintained or improved as increases	Coordination mechanisms may not scale beyond small groups	Critical for grid-scale deployment across geographically distributed infrastructure
Embodiment	Physical robots or direct physical analogs (e.g., UAVs, ground robots)	Includes pure software agents without physical counterpart	Only physically embodied agents interact with physical grid infrastructure

Based on this taxonomy, the inclusion criteria for this review explicitly require that included studies involve physically embodied agents (robots, UAVs, or direct physical analogs) or swarm intelligence algorithms (PSO, ACO, consensus control) applied to energy or grid optimisation problems. Pure software multi-agent systems without physical embodiment are included only as a clearly identified sub-category when the algorithmic contribution is directly applicable to physical swarm deployment in grid contexts.

2.3. Literature Synthesis and Classification Framework

The integration of renewable energy sources, such as solar and wind, into the electrical grid has presented a significant challenge for power system operators and engineers. The widespread use of Renewable Energy Sources (RES) demands a fundamentally different approach to energy network management [11]. Traditional power grids were designed to accommodate centralised, dispatchable generation, but the intermittent and variable nature of renewable energy resources requires a more flexible and responsive grid infrastructure. The emergence of smart grid technologies has the potential to address these challenges and facilitate the widespread adoption of renewable energy. These systems can actively monitor and manage the flow of electricity, enabling enhanced incorporation of sustainable energy resources. Additionally, smart grids can enable customers to take an active role in the energy system through features such as real-time pricing and demand-side management, further supporting the integration of renewable energy. Figure 2 showcases an example of a smart grid incorporating Renewable Energy Sources, illustrating the interconnection between generation sources (solar, wind, and conventional thermal), the transmission and distribution network, smart metering infrastructure, and end consumers. This architecture forms the operational context within which swarm robotic systems—as reviewed in Section 3—are proposed to assist with monitoring, maintenance, and energy flow optimisation. In particular, the distributed nature of renewable generation nodes and the geographic extent of transmission infrastructure create natural deployment opportunities for swarm agents operating under local communication constraints.

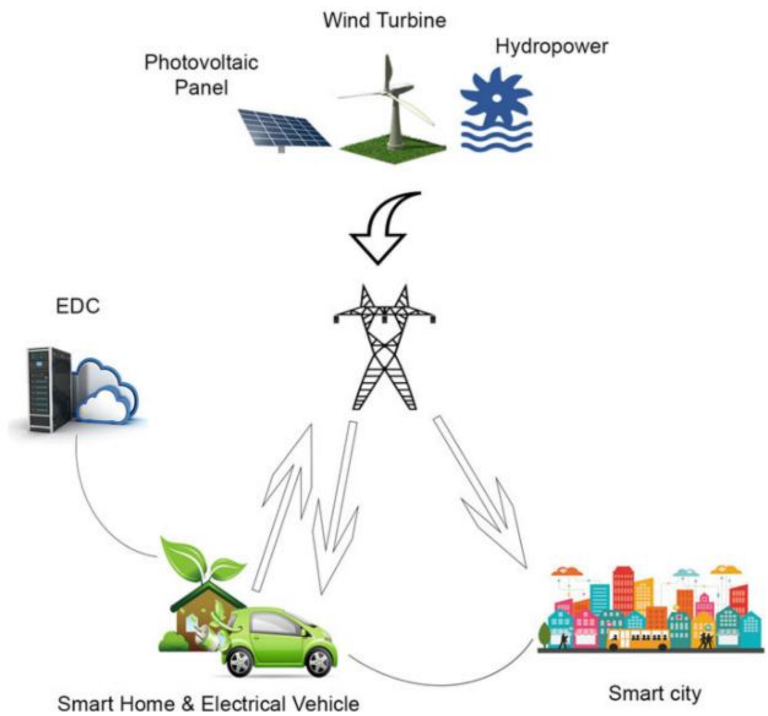

Figure 2. General layout of smart grid using renewable energy sources.

Several countries have implemented policies and regulations to support the development of smart grids and the integration of renewable energy. These efforts include establishing renewable energy targets, providing financial incentives for grid modernisation, and implementing regulations to ensure data security and privacy. As described by Brown and Zhou, "*smart grid policies include a new generation of regulations and finance models such as regulatory targets, requirements for data security and privacy, renewable energy credits, and various interconnection tariffs and utility subsidies*" [12].

While the transition to a smart grid-enabled renewable energy system presents technical, regulatory, and financial challenges, the potential benefits are significant. As outlined by Amin, smart grids can decrease the amount of electricity consumed when not in use and enable utilities to better integrate and act on the massive amount of data in order to enhance system reliability, further supporting the integration of renewable energy. With the increasing urgency of addressing climate change and the growing demand for clean, sustainable energy, the development of smart grid infrastructure is crucial to facilitating the widespread adoption of renewable energy sources [13].

The transformation of traditional power grids into smart grids has been a significant focus in the energy industry, driven by the need to improve efficiency, reliability, and sustainability [14]. Smart grids, as described in the literature, are characterised by the integration of information and communication technologies (ICT) with power grid infrastructure [15]. This concept enables greater interaction between utilities and consumers, facilitating real-time data exchange and advanced control functions [16]. The incorporation of smart devices, such as sensors and smart metres, into the grid allows for improved monitoring, data collection, and automated decision-making, ultimately enhancing the overall efficiency of the power distribution system.

The integration of renewable energy sources, such as solar, wind, and hydropower, into the electric grid has presented both opportunities and challenges for the development of smart grid systems [11]. Smart grid technology aims to enhance the reliability, efficiency, and sustainability of power generation and distribution, while also accommodating the intermittent and variable nature of renewable energy sources. One key aspect of smart grid technology in renewable energy systems is energy management [17]. Smart grids use the Internet of Things (IoT) and advanced communication systems to optimise the integration of renewable energy, improving energy efficiency, maximising resource utilisation, and reducing costs. This is achieved through strategies such as demand-side management, which allows for dynamic pricing and load balancing to match supply and demand [9].

Smart grids also have a critical role in enhancing the reliability of renewable energy systems. By incorporating energy storage and distribution automations, smart grids can better manage the fluctuations inherent in renewable generation, ensuring a more stable and reliable power supply. Additionally, the microgrid architecture of smart grids enables the integration of various distributed energy resources, including renewable sources and storage systems, improving the overall resilience of the power system [18].

Another important aspect is the integration of smart grid technologies to facilitate the seamless incorporation of renewable energy [19]. Smart grid systems leverage advanced metering, communication, and control technologies to monitor and manage the bi-directional flow of electricity, accommodating the variable nature of renewable generation [11]. This dynamic management of the grid allows for the efficient and reliable integration of renewable energy sources, even in areas remote from population centres.

A major factor driving the adoption of smart grids is the growing complexity of the energy sector, influenced by trends like population growth, the rising demand for a higher standard of living, and constant technological progress. As a result, there has been a steady increase in energy consumption, putting considerable pressure on the existing power grid system. The smart grid seeks to tackle these issues by fostering better interaction between the grid and consumers, supporting the integration of renewable energy sources, and enhancing overall energy efficiency through smart control and decision-making [20]. Nonetheless, the shift to smart grids also introduces new security concerns that must be carefully managed to protect vital infrastructure.

In modern way of life, electricity is a basic commodity for almost all human activities, making a stable and secure power supply vital. Since electrical energy is difficult and costly to store in large amounts, electrical systems must maintain a constant balance between production and consumption. The smart grid seeks to solve this issue by facilitating the integration of renewable energy sources and enhancing energy efficiency through advanced control and decision-making processes. By combining information and communication technologies with more advanced electrical grid infrastructure, smart grid technology improves the overall performance of the grid, ensuring greater system reliability and efficiency [21].

3. Swarm Robotics Used in Smart Grids

Swarm robotics, an emerging field in the realm of robotics, has garnered significant attention in recent years due to its ability to tackle complex problems through the coordination and collaboration of multiple autonomous agents. This approach, inspired by the collective behaviour of social insects, enables a group of simple robots to outperform a single, more complex robot in various tasks, offering robustness, flexibility, and efficiency. One of the defining characteristics of swarm robotic systems is their decentralised and distributed nature, where individual robots interact with their local environment and neighbouring robots to achieve a common goal. This self-organising behaviour, facilitated by the use of local rules and interactions, allows the swarm to adapt to changing conditions and overcome the limitations of individual robots [22].

Robotics has increasingly been applied to smart grid infrastructure inspection, maintenance, and the integration of renewable generation assets [23]; the growing interconnection of these systems has, in turn, heightened attention to cybersecurity policy [24] and to the role of energy storage in absorbing renewable-generation variability [25]. The remainder of this section reviews the primary corpus identified in Section 2 across the four application domains introduced in Table 2: monitoring and inspection (Section 3.1), energy distribution optimisation (Section 3.2), fault detection and resilience (Section 3.3), and cybersecurity and communication (Section 3.4).

Numerous research advancements have been made in the field of swarm robotics, as evidenced by the wide range of applications and experimental results reported in the literature. These studies have explored various aspects of swarm robotics, including modelling methods, swarm robotic entity projects, simulation platforms, and cooperative control mechanisms for flocking, navigation, and search tasks. However, none of them is dedicated to smart grid but more general purposes.

Indicative:

- Sambots have the ability to self-assemble and self-reconfigure to create new structures. The team's inventive docking mechanism design and thoughtful distribution of the perception system allowed them to build the robots [26].
- The I-SWARM Project: Intelligent Small World Autonomous Robots for Micro-manipulation. In this project, micro-robots may be produced in large quantities and utilised as a genuine swarm with over 100 micro-robots. All of these micro-robots have inadequate intellect and sensors. Because of its small size, the swarm can collaborate in a small globe at a very low cost.

- The e-puck is a robot which is designed for education in the field of engineering. This project's primary objective is to create a tiny, mobile robot for educational purposes. The robots have a number of characteristics designed specifically for this use. The robots' neat mechanical design makes them easy to use, maintain, and comprehend. Because of their many sensors, processing capabilities, and expansions, the inexpensive, adaptable robots may be used for a wide range of instructional tasks [27].
- The University of Stuttgart created the open hardware robot Jasmine with the intention of creating an accessible and affordable micro-robot platform [28].
- Kobot is self-organised flocking in a swarm of mobile robots. The robots are outfitted with a revolutionary short-range sensing system that uses infrared technology to measure the distance between obstacles and the relative directions of nearby robots [29].
- Pi Swarm is a platform designed for swarm robotics instruction and research. Its goals include lowering costs and streamlining the toolchain and platform programming [30].
- mROBerTO 2.0. is a robotic system with sophisticated sensing and processing capabilities to develop swarm robotics applications. Developments on this platform made it possible to create platforms with repeatable and more dependable movement [31].
- Tribots are three-legged robots intended to mimic the intricate ant techniques, such as dodging massive predators. The robots are simple to construct and are sized like insects. However, it permits a collection of five distinct motions [32].
- Khepera was developed in the mid-1990s. It was one of the earliest robotic initiatives. Over the following ten years, other versions, such as Khepera III, were released along with a few simulation programmes. In an upgraded version, Khepera IV is enhanced with an 800 MHz ARM Cortex-A8 Linux Core Processor, 256 MB RAM, an extra 512 MB and 8 GB data flashcard, 802.11 b/g Wi-Fi, Bluetooth 2.0 EDR, and 20 sensors [33,34].
- ALICE. Gilles Caprari of the EPFL Autonomous Systems Lab developed Alice as an improvement to Khepera. It was a tiny, autonomous robot that gained a lot of popularity because of its affordability and size, which made it feasible to create and oversee a large number of robots at once [35].

Table 5 summarises the reviewed swarm robot platforms, distinguishing demonstrated grid deployments from potential or hypothetical applicability via two columns: "Demonstrated Grid Deployment" (Yes/No) and "Grid Adaptation Potential (Rationale)". For general-purpose platforms such as e-puck, Khepera, ALICE, Jasmine, and Pi Swarm, demonstrated grid deployment is recorded as "No", since these platforms were developed for education or general swarm robotics research rather than for smart grid applications; the rationale column identifies which technical characteristics (e.g., wireless communication capability, scalability, decentralised control) make each platform conceptually relevant to future grid applications.

Table 5. Pros and cons of the implemented swarm robots.

Name	Pros	Cons	Demonstrated Grid Deployment	Grid Adaptation Potential (Rationale)
Sambots	Self-assembly Self-reconfiguration	Has not been tested on large number of robots	No	Physical reconfiguration allows local grid hardware to adapt dynamically to environmental changes.
I-SWARM	Small size Hierarchical swarm control	Works in a small and specific area	No	Highly applicable for high-density sensor grids or micro-electronic component inspection.
e-puck	Open-source software Open hardware	Educational robot	No	Highly modular bench-test platform for simulating decentralised swarm algorithms.

Jasmine	Can be extended	Wireless communication via IR	No	Low-cost platform suitable for testing high-density localised routing algorithms.
Kobot	Wireless parallel programming system 10 h battery life	Sensing system needs to be improved	No	Long battery life is ideal for testing long-duration local flocking and spatial distribution.
Pi Swarm	Dynamic recharging Scalability	RF-based communication	No	Dynamic recharging is a critical feature for continuous, autonomous grid asset monitoring.
mROBerTO 2.0	Reliable motion High speed	Limited time operation	No	Advanced onboard sensing is ideal for rapid-response substation or localised circuit inspections.
Tribots	Navigation	No camera	No	Legged locomotion provides adaptation potential for traversing complex, rough outdoor terrains.
Khepera	Sensing capabilities, Extensions	Moving only in flat surfaces	No	High computational power (ARM) allows onboarding edge-processing algorithms.
ALICE	Cooperation	Laboratory conditions	No	Extremely small scale enables physical laboratory testing of massive multi-agent coordination.

3.1. Monitoring and Inspection

Ant Colony Optimisation (ACO), introduced by Dorigo et al. [36], simulates the pheromone-based path selection behaviour of ant colonies to solve combinatorial optimisation problems. In multi-robot grid applications, ACO has been applied to task allocation for infrastructure inspection, to optimal routing in grid communication networks, and to fault isolation in distribution networks, where the distributed nature of the algorithm aligns naturally with the decentralised architecture of swarm systems [36]. A related multi-objective approach is taken by Landa-Torres et al. [37], who schedule inspection tasks across a swarm of robots using heuristic solvers (a multi-objective harmony search method and NSGA-II) that explicitly account for each robot's mission cost—battery consumption and mechanical wear—alongside task completion time.

PSO has also been applied to multi-AUV cooperative path planning: Sun and Lv [38] combine an improved multi-objective PSO with a dynamic-window local planner for AUVs operating in three-dimensional terrain with ocean currents, reducing path length by 15.5% relative to a traditional PSO baseline. As with UAV-based inspection, deployment of these approaches is constrained by bandwidth: bandwidth demand scales with swarm size, and a fleet of 20 inspection UAVs, each transmitting HD video at 4 Mbps, generates 80 Mbps of aggregate data—substantially exceeding the capacity of typical grid communication networks. Ahmed et al. [39] review UAV-based inspection methods for power transmission lines and highlight onboard data processing and deep-learning-based defect detection as key enablers for reducing reliance on manual, helicopter-based inspection, alongside battery endurance and adverse-weather operation as recurring practical constraints.

3.2. Energy Distribution Optimisation

Particle Swarm Optimisation (PSO), originally proposed by Kennedy and Eberhart [40], is a population-based metaheuristic inspired by the collective movement of bird flocks and fish schools. Each particle (candidate solution) adjusts its trajectory based on its own best-known position and the swarm's global best, converging toward an optimum over successive iterations [40,41]. The Bees Algorithm [41], a related bio-inspired approach, has similarly been applied to engineering optimisation problems relevant to energy systems. del Valle et al. [42] provide a comprehensive survey of PSO variants applied to power systems, demonstrating convergence advantages over genetic algorithms in non-convex optimal power flow problems. More recently, Paul et al. [8] applied a quantum-inspired variant of PSO (QPSO) to day-ahead optimal energy management in a grid-connected microgrid incorporating photovoltaic, wind, fuel-cell and battery-storage units, reporting a 9.67% reduction in operational costs and a 13.23% reduction in carbon emissions relative to a differential-evolution baseline.

Interface with SCADA and EMS Infrastructure

Pattern 1—Direct integration: swarm agents publish sensor readings and receive set-points through the existing SCADA communication fabric using standardised protocols such as IEC 61850 or DNP3. This approach minimises integration overhead but requires that swarm agent communication comply with grid communication security requirements and latency constraints. Pattern 2—Edge-gateway architecture: a local edge node aggregates swarm sensor data and translates it into SCADA-compatible formats, reducing bandwidth demands on the SCADA network and decoupling swarm communication protocols from grid protocols. Pattern 3—Parallel monitoring layer: swarm data is processed independently and results (fault flags, maintenance alerts, anomaly detections) are fed into the EMS as advisory inputs without modifying the primary control loop. This is the most commonly described architecture in the reviewed literature, particularly for inspection applications, because it does not require modification of the primary grid control system [43,44].

The reviewed literature predominantly describes Pattern 3 for inspection applications and Pattern 2 for energy optimisation applications. Direct integration (Pattern 1) remains largely aspirational in the reviewed studies and represents an open research challenge: it requires that swarm agent communication be formally verified for security and reliability under grid cybersecurity standards (NERC CIP, IEC 62351), which do not yet specifically address swarm robot integration. This regulatory gap is identified as a future direction in Section 4.

3.3. Fault Detection and Resilience

Consensus-based distributed control, formalised by Olfati-Saber et al. [45], provides a mathematically rigorous framework for achieving agreement among networked agents without centralised coordination. Each agent updates its state as a weighted average of its own value and those of its neighbours, converging to a common value under connected graph topologies. In microgrid applications, consensus protocols have been applied to distributed frequency regulation, voltage control, and energy balancing [46,47]. Tuballa and Abundo [46] review the development of smart grid technology and identify distributed coordination as a key challenge; Mahmoud et al. [47] provide modelling and control frameworks for microgrids that underpin consensus-based approaches. Alghamdi [10] demonstrated a distributed consensus-based voltage and frequency controller for an isolated microgrid with induction-motor loads, reducing frequency deviation from 0.45 Hz to 0.15 Hz under sudden load increases and cutting post-fault voltage-recovery time by 56% (from 2.5 s to 1.1 s), while remaining stable under communication delays of up to 500 ms. Consensus-based approaches have also been applied to demand response coordination [48], where distributed agents negotiate load reduction commitments without a central aggregator, improving grid stability under high renewable penetration. The formal convergence guarantees of consensus algorithms—which require that fewer than half of the agents fail simultaneously—make them particularly attractive for safety-critical grid control applications [10,45,47].

Packet loss has been identified as a further concern: consensus-based algorithms maintain convergence guarantees when packet loss remains below approximately 10–20%, but performance degrades sharply beyond this threshold [45].

3.4. Cybersecurity and Communication

The deployment of swarm robotic systems in smart grid environments introduces specific communication challenges that differ from laboratory conditions. Yan et al. [49] survey the communication infrastructure requirements of smart grids, identifying four critical parameters: latency, bandwidth, reliability, and security. For swarm systems, these parameters interact in ways that can fundamentally affect coordination performance.

Latency is a critical constraint for real-time grid control. Primary frequency regulation requires sub-100 ms response times, while protection systems demand sub-20 ms. Swarm consensus algorithms, which require multiple communication rounds to converge, may not meet these requirements over high-latency wireless links. IEEE 802.11ah (Wi-Fi HaLow) and 5G NR sidelink protocols offer latencies below 10 ms at ranges up to 1 km, making them candidate communication layers for swarm–grid integration [49,50]. Tightiz and Yang [50] provide a comprehensive review of IoT protocols in the smart grid context, evaluating their suitability for latency-sensitive coordination tasks. Wireless sensor deployment strategies for large-area coverage—such as the cat-swarm-optimisation-based approach of Temel et al. [51] for maximising sensing coverage while minimising the number of deployed sensors on 3D terrain—are directly applicable to positioning swarm agents across grid infrastructure. Co-channel interference between swarm robot radios and existing grid SCADA systems, which typically operate over both licenced wireless spectrum and power line communication (PLC) infrastructure [52], requires careful frequency coordination [49,53]; spectrum-aware networking approaches [53] have been proposed specifically for environments where industrial wireless systems and grid control systems share spectrum. Swarm intelligence methods have themselves been applied to routing optimisation in wireless sensor networks deployed in grid environments, as surveyed by Saleem et al. [54]. Peer-to-peer energy trading platforms such as the Brooklyn Microgrid [55] represent an application domain where low-latency distributed communication is equally critical.

The integration of swarm robotic systems with smart grid infrastructure introduces cybersecurity risks that extend beyond those of conventional grid SCADA systems. Mo et al. [56] identify the cyber-physical nature of smart grid attacks as a defining characteristic: adversaries can exploit digital communication channels to cause physical damage to grid infrastructure. In swarm systems, the distributed and wireless nature of inter-agent communication creates additional attack surfaces not present in centralised systems.

Three threat models are particularly relevant to swarm–grid systems. First, Sybil attacks [57] involve a malicious entity impersonating multiple swarm agents, thereby distorting the consensus process by introducing false readings that appear to originate from multiple independent sources. Second, Byzantine faults [58]—in which compromised agents transmit arbitrary or strategically misleading information—can destabilise distributed control loops. Byzantine-fault-tolerant consensus algorithms require that fewer than one-third of participating agents be compromised simultaneously to maintain correct operation [58]. Third, denial-of-service attacks targeting the wireless communication links between swarm agents can prevent consensus convergence, potentially causing loss of coordinated control during grid emergencies. Fourth, physical compromise of robots operating in accessible field locations—such as substations, wind farms, and solar installations—represents a threat vector with no equivalent in purely software-based systems; a physically compromised agent can be reprogrammed to act as a Byzantine agent or to relay incorrect sensor data [56].

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Mitigation strategies identified in the reviewed literature include: cryptographic identity management for agent authentication to prevent Sybil attacks; anomaly detection based on cross-validation of neighbouring agent readings to identify Byzantine behaviour; and frequency-agile communication protocols to maintain connectivity under jamming conditions. It is noted that the current smart grid cybersecurity standards framework (NERC CIP, IEC 62351) does not yet specifically address swarm robot integration, representing a regulatory gap that requires attention as these systems approach deployment scale [56].

4. Discussion

Swarm robotics offers a decentralised and resilient approach to the dynamic, adaptive control problems inherent to smart grid operation. This is particularly relevant given the uncertainty and variability that renewable energy sources such as solar and wind introduce into grid supply-and-demand balancing [11]. By leveraging the self-organising coordination principles that characterise swarm systems more generally [2], smart grid operators can, in principle, develop control strategies that respond to fluctuations in supply and demand without relying on a single point of centralised control. The evidence reviewed in Section 3, however, indicates that this potential is realised unevenly across the four application domains considered in this review.

Energy distribution optimisation and fault detection and resilience currently offer the strongest quantified evidence among the four domains considered in this review: Paul et al. [8] report a 9.67% reduction in operational costs from quantum-inspired PSO scheduling (Section 3.2), and Alghamdi [10] reports a 66% reduction in frequency deviation and a 56% faster post-fault voltage recovery from consensus-based control (Section 3.3). Monitoring and inspection applications (Section 3.1) show comparable methodological maturity: Landa-Torres et al. [37] incorporate mission-cost factors such as battery consumption directly into swarm task scheduling, and Sun and Lv [38] report a 15.5% reduction in path length for cooperative multi-AUV navigation relative to a traditional PSO baseline. In all three domains, however, these results come from simulation studies or small-scale testbeds rather than field deployments.

The global literature does not contain many examples that would be useful for the application of robotic swarm systems in smart grids, although there is clear potential for their use. Nonetheless, our study shows there is a significant opportunity for optimising these systems, both in maintenance and monitoring, and also in improving their overall efficiency. The reviewed literature reveals a consistent and significant gap between laboratory-scale demonstrations and utility-scale deployment of swarm robotics in smart grids. The majority of reviewed studies validate their approaches with fewer than 20 physical agents in controlled environments, and none report full integration with operational SCADA or Energy Management System (EMS) infrastructure. This gap has important implications for claims of scalability, which must be interpreted carefully in the context of the evidence available.

Three scalability-limiting factors emerge consistently from the reviewed literature. First, communication graph connectivity degrades as agent density decreases over large geographic areas, such as those typical of transmission infrastructure inspection. Second, distributed consensus algorithms exhibit worst-case message complexity that grows with the number of agents, which becomes prohibitive for real-time grid control contexts with more than approximately 50–100 agents communicating over bandwidth-constrained wireless links [45,49]. Third, energy autonomy of individual agents limits operational duration in field deployments; current inspection UAVs typically operate for 20–40 min per charge, requiring either stationary charging infrastructure distributed across the inspection area or heterogeneous swarm architectures incorporating dedicated recharging agents [39,59]. Albaker and Rahim [59] survey collision avoidance approaches for UAVs

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that are directly applicable to swarm navigation in constrained grid environments. These constraints define the practical operating envelope for current swarm–grid systems and highlight the directions in which engineering progress is most urgently needed. Promising directions identified in the reviewed literature include peer-to-peer energy trading architectures [55,60], where Zafar et al. [60] demonstrate prosumer-based energy sharing mechanisms compatible with swarm-coordinated distributed generation; coordinated energy management across networked microgrids [43]; localisation-assisted swarm coordination [61]; and distributed DC microgrid control [62]. The integration of plug-in electric vehicles as distributed energy resources [63] and the application of intelligent control to grid frequency stabilisation [64] further illustrate the performance targets that swarm-based solutions must meet to achieve practical deployment at utility scale. Smart grid surveys [44] provide the broader context within which these contributions must be situated.

5. Conclusions

This review synthesised the swarm robotics literature relevant to smart grid operation across four domains: monitoring and inspection, energy distribution optimisation, fault detection and resilience, and cybersecurity and communication. Energy distribution optimisation and fault detection and resilience currently offer the strongest quantified evidence: quantum-inspired PSO scheduling achieves a 9.67% operational-cost reduction and a 13.23% emissions reduction [8], and consensus-based voltage/frequency control achieves a 66% reduction in frequency deviation and a 56% faster post-fault voltage recovery [10], though neither has been demonstrated beyond simulation or small-scale testbeds, or at multi-microgrid/utility scale. Monitoring and inspection shows comparable methodological maturity: heuristic task-scheduling methods explicitly account for mission cost such as battery consumption [37], and hybrid PSO path planning reduces path length by 15.5% relative to a traditional PSO baseline [38]. Fault detection and resilience also offers formal convergence guarantees under bounded packet loss (below 10–20%) [45] and Byzantine fault tolerance for up to one-third compromised agents [58], but published evaluations remain confined to small testbeds of fewer than 20 agents. Cybersecurity and communication is the least mature of the four domains: threat models (Sybil, Byzantine, denial-of-service, physical compromise) and mitigation strategies are well characterised conceptually, but no reviewed study reports a field-validated security architecture for swarm–grid integration, and existing regulatory frameworks (NERC CIP, IEC 62351) do not yet address swarm robot integration.

Three concrete recommendations follow from these findings. First, because Pattern 3 (parallel monitoring layer) integration with SCADA/EMS infrastructure is by far the most mature architectural pattern in the reviewed literature, near-term deployment efforts should prioritise this pattern over the largely aspirational Pattern 1 (direct integration), while treating the formal security verification needed for Pattern 1 as a distinct research objective rather than an incidental byproduct of deployment. Second, because the reviewed evidence shows a sharp transition in consensus algorithm reliability beyond approximately 50–100 agents and above 10–20% packet loss, future field trials should explicitly report swarm size and communication reliability alongside performance metrics, so that scalability claims can be compared and verified across studies. Third, given the near-total absence of field-validated cybersecurity evaluations, we recommend that funding bodies and standards organisations treat swarm-specific extensions to NERC CIP and IEC 62351 as a priority research and policy gap, rather than deferring it as a downstream implementation detail.

Future work should prioritise field trials beyond the fewer-than-20-agent, laboratory-scale envelope that characterises the current literature, with explicit reporting of communication reliability, agent count, and SCADA/EMS integration pattern (direct, edge-gateway, or parallel-monitoring), so that scalability and deployment-readiness claims can be compared across studies on a consistent basis.

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