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SWARM INTELLIGENCE OPTIMISATION VS DEEP LEARNING: ENERGY-AWARE STRATEGY FOR DISASTER COMMUNICATION NETWORKS

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ABSTRACT
In disaster-prone environments, communication networks must sustain operation under severe constraints such as limited energy, damaged infrastructure, and uncertain topology. This study compares Deep Learning (DL) and Swarm Intelligence Optimisation (SIO) as energy-aware strategies for disaster communication. While DL excels in data-rich prediction and situational analysis, its reliance on high-performance hardware and stable connectivity restricts its feasibility during real-time emergencies. In contrast, SIO provides decentralised coordination, lightweight computation, and adaptive routing, making it better suited to infrastructure-independent device-to-device (D2D) networks when central control collapses. A comparative conceptual framework was developed to evaluate both paradigms across five criteria: energy efficiency, adaptability, computational demand, response time, and scalability, based on recent literature between 2023 and 2025. Findings show that SIO demonstrates superior suitability for energy-limited and time-critical operations, while DL remains valuable for pre-disaster prediction and post-event analysis. Hybrid DL–SIO frameworks bridge both paradigms, enabling predictive–adaptive synergy across the disaster lifecycle. The study contributes a context-aware guideline for algorithm selection, shifting the focus from technology-centric performance toward environment-centric deployment in future energy-efficient, resilient, and adaptive disaster communication systems.
Keywords: *Swarm Intelligence Optimisation, Deep Learning, Disaster Communication, Energy-Aware Networks, Device-to-Device Communication.*

1. Introduction

Both natural and anthropogenic disasters pose recurring challenges to the resilience of global communication systems. According to the United Nations Office for Disaster Risk Reduction (UNDRR, 2023) more than 350 major disasters are recorded annually worldwide, disrupting essential communication infrastructure and isolating affected populations. During catastrophic events like earthquakes, hurricanes, and floods, power outages and base-station failures frequently paralyse conventional cellular and Internet services (International Telecommunication Union, 2024). Recent studies estimate that over 65 percent of communication infrastructure in disaster-prone regions suffers partial or complete outage within the first 48 hours after impact (Q. Wang et al., 2023). In such environments, maintaining situational awareness and coordination among emergency responders becomes impossible without autonomous and self-organising communication systems operating without centralised control.

Conventional network architectures, which depend on central base stations or cloud servers, are often ineffective under these conditions. Their operation assumes a stable power supply, continuous backhaul connectivity, and high-capacity computing. These assumptions fail during crises (Debnath et al., 2022). As a result, research attention has shifted toward autonomous Device-to-Device (D2D) communication, where nodes interact directly to relay information and sustain connectivity. However, achieving reliable and energy-efficient D2D networking remains difficult because disaster environments are dynamic, resource-limited, and characterised by unpredictable topology changes. Energy depletion, inconsistent link quality, and the absence of central coordination often result in unstable routing and fragmented clusters, compromising communication continuity (Singh et al., 2021).

Artificial Intelligence (AI) has emerged as a promising adaptive and context-aware disaster communication enabler. Deep Learning (DL) and Swarm Intelligence Optimisation (SIO) represent two dominant but contrasting approaches among various AI paradigms. DL techniques such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Graph Neural Networks (GNNs) excel in pattern recognition, image classification, and large-scale prediction tasks (Lin et al., 2022; Saadati et al., 2024). These techniques are widely used for pre-disaster applications such as hazard mapping, damage assessment, and resource forecasting. However, DL models rely heavily on labelled datasets, high-performance hardware, and stable network connectivity (Antoniou & Potsiou, 2020). Their computational intensity and static nature after training limit their adaptability and make them unsuitable for real-time decision-making in resource-constrained post-disaster environments.

In contrast, SIO algorithms such as Particle Swarm Optimisation (PSO), Ant Colony Optimisation (ACO), Artificial Bee Colony (ABC), and Genetic Algorithms (GA) offer lightweight, decentralised, and self-adaptive optimisation inspired by collective biological behaviour (Gad, 2022; Tomar et al., 2023). These metaheuristics require minimal computational resources, operate without prior training data, and can dynamically adjust to environmental changes. In emergency communication systems, SIO has demonstrated effectiveness in cluster-head (CH) selection, energy-aware routing, and load balancing, which significantly prolongs network lifetime (Guleria & Verma, 2019; Z. Wang et al., 2020). Such features make SIO a compelling foundation for autonomous and resilient D2D communication when conventional infrastructure collapses. Fig. 1 compares the operational philosophy of DL and SIO. While DL is knowledge-centric and relies on pre-trained global models, SIO is behaviour-centric and driven by local cooperation and feedback. This fundamental difference underpins their contrasting suitability for pre-disaster analytics versus real-time emergency response.

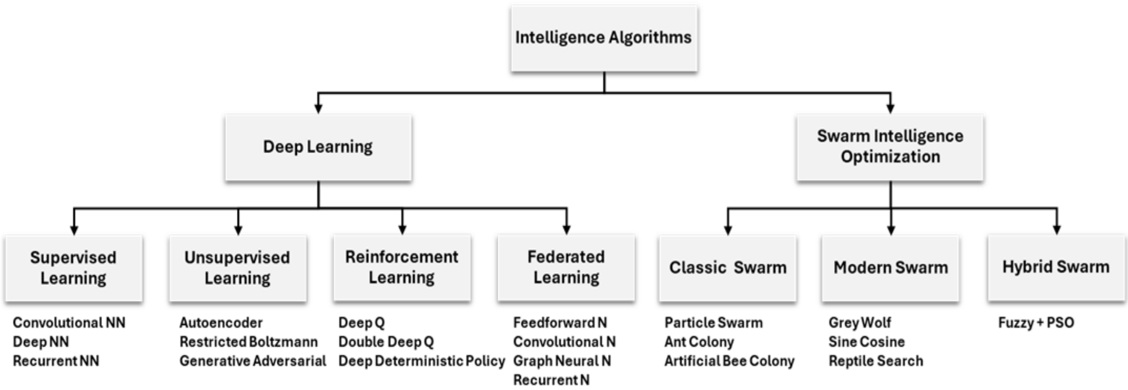

Fig. 1. Comparative taxonomy of Deep Learning (DL) and Swarm Intelligence Optimisation (SIO) paradigms for disaster communication.

Despite these complementary strengths, academic discourse remains fragmented. Several studies have promoted hybrid DL–SIO architectures that combine predictive learning with adaptive optimisation (Alqadhi et al., 2024; Işık et al., 2023). However, these works mostly target controlled simulation environments rather than real-world disaster contexts. Comprehensive reviews by (Ezugwu et al., 2022) and (Ahmad et al., 2024) reveal that most AI-based disaster communication frameworks still prioritise accuracy or throughput under ideal conditions while overlooking energy scarcity and decentralised deployment challenges. Furthermore, systematic evidence comparing the contextual suitability of DL versus SIO in disaster scenarios is scarce. Existing surveys evaluate performance metrics in isolation instead of establishing guidelines for algorithm selection based on environmental constraints. Consequently, practitioners and system designers often adopt data-intensive DL models in environments where lightweight, swarm-based optimisation would be far more practical.

This gap motivates the present study. Rather than following trend-driven integration of AI technologies, this paper advocates for context-driven algorithm selection that aligns with operational and environmental constraints. Specifically, it offers a conceptual comparative analysis between DL and SIO for energy-aware disaster communication networks. The study identifies both paradigms' strengths, weaknesses, and application boundaries. It introduces a context-aware decision-making framework to guide researchers and practitioners in choosing the most appropriate approach. This framework is grounded on four critical criteria: (i) energy availability, (ii) computational capacity, (iii) network stability, and (iv) time-critical adaptability. The study aims to enhance theoretical understanding and practical deployment of intelligent disaster communication systems by aligning algorithm choice with these real-world parameters.

The novelty of this work lies in shifting the narrative from technology-centric performance evaluation toward environment-centric suitability assessment. While previous research has primarily focused on improving algorithmic accuracy or developing hybrid models, this study reframes the problem through a contextual perspective that emphasises selecting the most appropriate intelligent approach for specific environmental conditions. The proposed framework contributes to the theory and practice of AI-driven disaster communication by offering a structured path for future empirical validation and adaptive algorithm design.

The remainder of this paper is organised as follows. Section 2 critically reviews recent literature on DL, SIO, and hybrid models in disaster communication. Section 3 details the conceptual methodology and comparative assessment framework. Section 4 discusses the results and strategic implications of algorithm selection under varying operational constraints. Section 5 concludes the paper with theoretical insights, practical recommendations, and directions for future research.

2. Literature Review

This section critically reviews recent developments in DL, SIO, and hybrid or emerging AI paradigms within disaster communication networks. The discussion integrates methodological advances with contextual constraints, focusing on how each paradigm aligns with infrastructure-independent systems' energy, computation, and adaptability demands. It is organised into five parts: (i) DL applications in disaster communication, (ii) SIO for energy-aware networking, (iii) hybrid and emerging AI models, (iv) theoretical foundation and research gaps, and (v) literature selection method.

2.1 Deep Learning in Disaster Communication

Over the past decade, DL has become the dominant AI paradigm for automated sensing, classification, and decision-making in disaster management. Techniques such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Graph Neural Networks (GNNs), and Transformer-based models have achieved state-of-the-art accuracy in flood-extent mapping, damage identification, and early-warning systems (Kyrkou & Theocharides, 2019; Lin et al., 2022; Saadati et al., 2024). Recent advances include lightweight CNN–LSTM pipelines for UAV-based situational analysis (Alqadhi et al., 2024) and multi-modal hazard prediction using satellite imagery ((Saleem et al., 2025).

Despite their analytic strength, DL models remain constrained in post-disaster operations. They require large, labelled datasets and GPU-intensive hardware, and depend on stable connectivity—conditions rarely met when infrastructure collapses. DL inference is computationally expensive and static after training, leading to latency in cluster-head (CH) selection or routing (Antoniou & Potsiou, 2020). Edge-AI frameworks attempt decentralisation (M. Li & Cheng, 2022), but energy and memory costs remain prohibitive for sustained emergency use. Moreover, DL's "black box" opacity limits transparency when human validation is urgently needed(Ezugwu et al., 2022).

Federated and distributed DL have recently been explored to mitigate central dependency. (J. Li et al., 2024) proposed a Federated Reinforcement Distillation-based Routing (FedRDR) that integrates federated learning with deep reinforcement learning for UAV-assisted networks, while (Alsaaran & Soudani, 2025) developed a MobileNetV3-Small model for UAV-based damage classification with real-time edge performance. These demonstrate promising autonomy yet remain limited by intermittent connectivity and finite onboard energy. In short, DL excels in data-rich pre-disaster analysis but struggles with real-time, energy-limited post-disaster coordination.

2.2 Swarm Intelligence Optimisation in Energy-Aware Networks

SIO SIO represents a class of bio-inspired metaheuristics such as Particle Swarm Optimisation (PSO), Ant Colony Optimisation (ACO), Artificial Bee Colony (ABC), and Genetic Algorithms (GA), characterised by decentralised control, self-adaptation, and robustness to uncertainty (Ahmed et al., 2024; Alshammri, 2025; Zhang et al., 2025). These qualities make SIO inherently compatible with disaster environments lacking central management.

In wireless sensor and D2D networks, SIO has been successfully applied to clustering, routing, and resource allocation. (Guleria & Verma, 2019) showed that an ACO-based unequal clustering scheme extended network lifetime by 28 %. (Singh et al., 2021) developed an adaptive GA for dynamic CH selection based on residual energy and node density. (Chao et al., 2020) introduced EAR, an energy-aware risk-averse routing framework using λ-optimal multipaths to balance delay and reliability. Collectively, these works prove that SIO can sustain performance with minimal computation and no reliance on pre-training.

Hybrid fuzzy–metaheuristic frameworks further enhanced SIO's adaptability. (Rawat et al., 2023) integrated fuzzy inference with PSO in FLPSOC, while (Azad et al., 2023) proposed PSO-AWDV, which accelerates convergence via dynamic inertia weighting and delayed velocity adaptation. Such methods maintain low complexity and high responsiveness, although scalability issues persist in dense networks. SIO's decentralised decision-making and energy efficiency make it the natural counterpart to data-driven DL in post-disaster settings.

2.3 Hybrid and Emerging AI Models

Hybrid approaches attempt to combine DL's predictive accuracy with SIO's adaptability. (Işık et al., 2023) fused ANN and PSO for seismic displacement prediction, achieving 99 % accuracy, while (Alqadhi et al., 2024) incorporated Explainable AI (XAI) into a CNN–LSTM for landslide forecasting. These outperform standalone models in laboratory settings but demand high computational resources.

Beyond DL–SIO hybrids, Reinforcement Learning (RL) and Edge AI extend adaptability. (Manogaran et al., 2025) proposed a federated double deep Q-learning routing scheme that improves latency and energy efficiency, while (L. Wang & Jiao, 2024) introduced a multi-agent RL offloading strategy for UAV networks. Similarly, (Cheriguene et al., 2025) reviewed Federated Learning (FL) as a distributed training paradigm that reduces dependence on a central data centre. Despite these advances, bandwidth synchronisation and connectivity requirements limit deployment in disaster zones. Hence, though conceptually powerful, hybrid and emerging AI models remain bounded by practical energy and coordination constraints.

2.4 Theoretical Foundation and Research Gap

This study is grounded in the theory of self-organisation and complex adaptive systems (CAS). Disaster-prone communication networks act as open, evolving systems where nodes locally adapt to maintain global stability (Deepak et al., 2019; Q. Wang et al., 2023). SIO naturally aligns with CAS dynamics through distributed, feedback-driven coordination, whereas DL relies on static, centralised training unsuited to dynamic environments.

A second underpinning is energy-aware optimisation theory, which seeks to minimise total power consumption while preserving throughput and reliability. (Omoniwa et al., 2022) applied decentralised multi-agent Q-learning for UAV base-station placement, while, (Lei, 2024) integrated fuzzy-PSO for energy-balanced IoT routing. These works confirm that swarm- and reinforcement-based mechanisms sustain equilibrium via distributed exploration, contrasting with DL's accuracy-centric optimisation.

Despite progress, gaps remain. Most studies evaluate algorithms by accuracy or convergence (Ahmad et al., 2024; Ezugwu et al., 2022) rather than contextual suitability. Few provide systematic guidelines for algorithm selection under environmental constraints. Consequently, disaster networks are often over-engineered with data-hungry DL systems ill-suited for field deployment. Table 1 summarises comparative insights between DL, SIO, and hybrid paradigms, while Figure 2 visualises their conceptual continuum from data-driven to optimisation-driven intelligence.

Table 1 – Comparative Insights of Deep Learning, Swarm Intelligence Optimisation, and Hybrid/Emerging AI

Criterion	Deep Learning (DL)	Swarm Intelligence Optimisation (SIO)	Hybrid / Emerging AI
Architecture	Centralised, data-driven	Decentralised, agent-based	Semi-distributed
Computation & Energy	High GPU/TPU demand	Lightweight, low energy	Moderate to high
Adaptability	Static after training	Real-time self-adaptive	Adaptive but complex
Data Requirement	Large, labelled datasets	Minimal or none	Moderate, may use partial data
Deployment Feasibility	Requires stable infra	Works under infra failure	Limited by resource coupling
Typical Use	Pre-disaster prediction, mapping	Real-time routing, clustering	Coordinated learning, decision-support

As shown in Table 1, DL offers predictive depth but lacks flexibility, SIO delivers adaptability with low energy overhead, and hybrids attempt to merge both at the expense of complexity. The contrast underscores the research gap motivating this study: a context-aware decision framework that aligns algorithmic properties with operational realities.

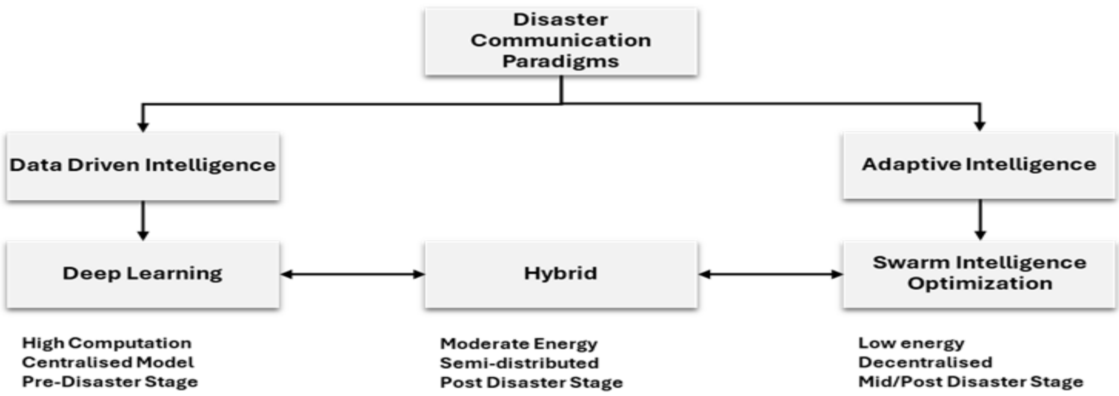

Fig. 2. Comparative Taxonomy of Deep Learning, Swarm Intelligence Optimisation, and Hybrid Paradigms for Disaster Communication.

Algorithm suitability in disaster communication cannot be generalised by accuracy or latency alone. Instead, it must be judged through energy availability, network stability, and computational feasibility principles that form the foundation of the comparative framework in Section 3.

2.5 Literature Selection Method

The study systematically explored scholarly literature using the Scopus database as the primary indexing source. A detailed search strategy was designed to capture publications on intelligent and energy-aware clustering algorithms in disaster-oriented wireless and device-to-device (D2D) communication networks. The TITLE-ABS-KEY query incorporated controlled terms and wildcards to ensure comprehensive coverage. The search string included keywords such as “deep learning”, “swarm intelligence”, “metaheuristic”, “energy-aware”, “clustering”, “device-to-device”, and “disaster communication”.

Table 2 – The Search Strings

Scopus	TITLE-ABS-KEY ((“deep learning” OR “swarm intelligence” OR “metaheuristic” OR “fuzzy logic” OR “reinforcement learning”) AND (“energy-aware” OR “clustering” OR “optimisation” OR “routing”) AND

	("disaster communication" OR "device-to-device network" OR "wireless sensor network"))

The search primarily targeted journal articles published between 2023 and 2025 in English, reflecting the most recent advancements in intelligent communication systems. However, several earlier studies predating 2023 were also included where their methodologies or findings were deemed highly relevant to the present research context. The final selection was refined to retain only articles addressing clustering algorithms, optimisation mechanisms, or AI-driven decision frameworks in disaster or wireless communication scenarios. The detailed search configuration is summarised in Tables 2 and 3.

Table 3 – The Selection Criteria for Searching

Criterion	Inclusion	Exclusion
Language	English	Non-English
Timeline	2023-2025	<2022
Literature type	Journal Article, Report	Proceeding, Book

3. Research Methods

The literature search and inclusion criteria are described in Section 2.5. The resulting articles served as the foundation for the comparative analysis in this section. This study employs a comparative analytical approach to examine the suitability of SIO and DL in energy-aware disaster communication networks. The aim is not to validate algorithms experimentally but to develop a logical, theory-driven justification for why SIO is better aligned with disaster communication environments' real-time, resource-constrained, and infrastructure-independent nature. This section describes how relevant literature was analysed, how comparative criteria were developed, and how the resulting insights were mapped to representative disaster scenarios.

3.1 Research Approach and Purpose

The research adopts a conceptual–comparative design. This approach is suitable because the goal is to evaluate existing paradigms based on their functional characteristics and operational context, rather than to test them empirically. DL and SIO have been widely implemented in communication and optimisation research, yet their contextual suitability under disaster conditions has rarely been compared within a unified framework.

The purpose of this methodology is therefore to:

1. Examine the functional and environmental attributes of each paradigm as reported in prior studies,
2. Identify core decision criteria that affect algorithm performance in disaster communication, and
3. Construct a context-aware framework for selecting the most appropriate paradigm in future algorithm design.

This design aligns with comparative reasoning approaches used in intelligent network research (Ahmad et al., 2024; Ezugwu et al., 2022) where conceptual justification precedes simulation-based validation.

3.2 Comparative and Contextual Evaluation Framework

To ensure an objective basis for comparison, the selected articles were examined using five primary evaluation criteria derived from recurring performance metrics in disaster-communication literature:

1. Energy Efficiency – indicates how algorithms minimise energy usage under a constrained power supply.
2. Adaptability – measures the ability to maintain performance despite topology or environmental changes.
3. Computation Demand – reflects processing and hardware requirements necessary for algorithm execution.

4. Response Time – captures how quickly the model can adapt or respond to network changes and node failures.
5. Scalability – assesses the capability to sustain performance as the number of devices or network size increases.

These criteria were chosen because they directly affect the feasibility of deploying intelligent algorithms in real-time disaster environments, where communication infrastructures are damaged and power sources are limited. Each article was coded according to whether it addressed these dimensions. The classification used a binary scheme: a tick (✓) when a criterion was explicitly discussed or measured, and a dash (–) when it was absent or not central to the study. This method allows the construction of an evidence-mapping matrix that identifies research trends and technological gaps between DL and SIO paradigms.

Table 4 – Literature Mapping Matrix

Article	Energy Efficiency	Adaptability	Computation Demand	Response Time	Scalability	DL/SIO	Context
(Ahmed et al., 2024)	✓	✓	–	–	✓	SIO	Post-disaster routing
(Alqadhi et al., 2024)	–	✓	✓	–	–	DL	Pre-disaster prediction
(Alsaaran & Soudani, 2025)	✓	✓	✓	–	✓	DL	Post-disaster analysis
(Azad et al., 2023)	✓	✓	✓	✓	✓	SIO	Real-time control
(Işık et al., 2023)	✓	–	–	–	–	DL & SIO	Real-time tracking
(Lei, 2024)	✓	✓	✓	✓	✓	SIO	Real-time routing
(M. Li & Cheng, 2022)	–	✓	✓	–	–	DL & SIO	Pre-disaster prediction
(Lin et al., 2022)	–	✓	–	–	–	DL	Real-time routing
(Omoniwa et al., 2022)	✓	✓	–	–	✓	DL	Real-time optimisation
(Rawat et al., 2023)	✓	–	–	–	–	SIO	Real-time clustering
(Saadati et al., 2024)	✓	–	–	–	–	DL	Dense network optimisation
(Singh et al., 2021)	✓	✓	✓	✓	✓	SIO	Post-disaster management
(L. Wang & Jiao, 2024)	✓	✓	✓	✓	✓	DL	Post-disaster rescue
(Zhang et al., 2025)	✓	✓	✓	✓	✓	SIO	Real-time response

A context-aware decision framework was developed to translate these comparative findings into actionable guidance. It summarises how environmental conditions and operational constraints determine the optimal choice between DL, SIO, and hybrid approaches. The framework illustrates a logical decision flow for selecting the appropriate paradigm. DL is preferred when the environment is stable and data-rich; SIO is prioritised when energy constraint and real-time responsiveness are critical; while hybrid SIO + DL is suitable when predictive accuracy and adaptability are required.

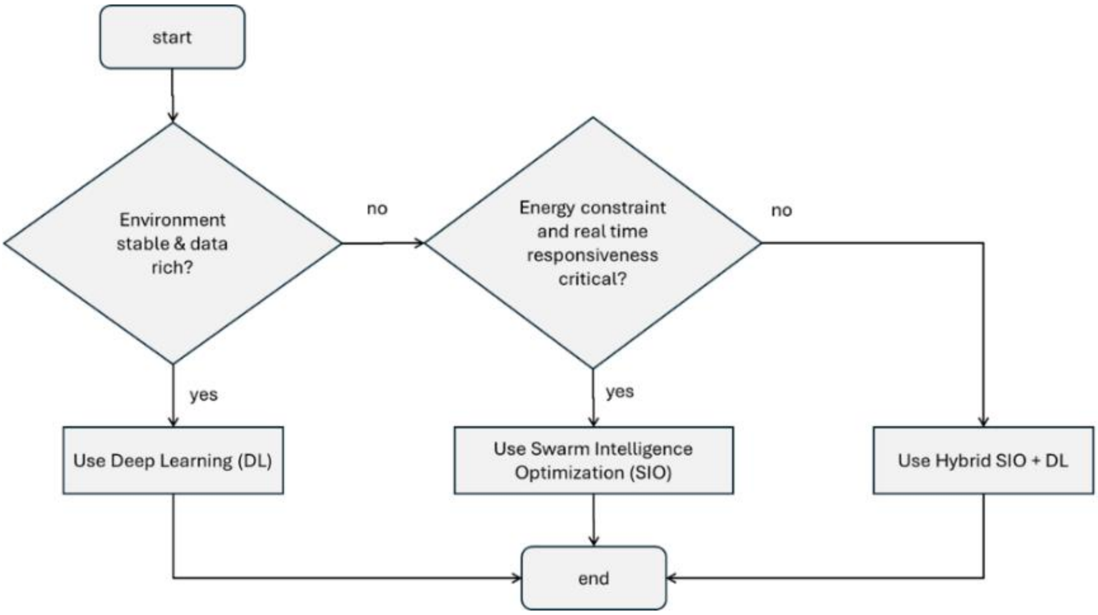

Fig. 3. A Context-aware Algorithm Selection Framework for Disaster Communication Networks

The mapping in Table 4 and the decision flow in Fig. 3 illustrate how algorithmic properties correspond to operational needs in disaster communication. SIO-oriented studies such as (Ahmed et al., 2024), (Lei, 2024), and (Zhang et al., 2025), emphasise low-energy operation, adaptive routing, and rapid convergence, all crucial for maintaining autonomy under severe power constraints and collapsed infrastructure. DL-oriented works, including (Alqadhi et al., 2024) and (Alsaaran & Soudani, 2025), excel in data-rich analytical phases but are limited by high computation and communication overhead during real-time deployment. Hybrid efforts like (Işık et al., 2023) and (M. Li & Cheng, 2022), attempt to merge predictive learning with adaptive optimisation to bridge these paradigms.

Comparative trends show that most SIO studies prioritise energy efficiency, adaptability, and rapid response, whereas DL studies focus on data modelling and predictive accuracy. This divergence confirms that the two paradigms are complementary rather than competitive, serving distinct stages of the disaster-management cycle. SIO is more effective in real-time and post-disaster operations, where stability depends on decentralised decision-making and minimal energy use. DL is more suitable for pre-disaster forecasting and post-event analysis, where computation and data resources are abundant. Therefore, algorithm selection should be guided by accuracy metrics and environmental context, energy availability, and mission urgency.

Recent hybrid frameworks demonstrate increasing interest in integrating DL’s predictive capability with SIO’s adaptive resource control to form resilient, context-aware communication systems capable of predicting, adapting, and reacting dynamically throughout a disaster cycle. However, hybridisation increases computational complexity, demanding further exploration to balance accuracy with feasibility. The mapping and decision framework jointly provides a structured, context-sensitive interpretation of algorithm suitability for disaster communication networks. They establish a clear analytical foundation for the theoretical implications and strategic recommendations discussed in Section 4.

4. Results and Discussions

The comparative synthesis presented in Section 3 provides the foundation for analysing the contextual relationship between algorithmic characteristics and disaster communication requirements. This section expands that interpretation into a deeper theoretical discussion, focusing on three dimensions: environmental suitability, operational performance, and strategic applicability to explain how DL, SIO, and hybrid models align with the realities of disaster communication systems.

4.1 Environmental Suitability and Energy Dependence

The findings indicate that SIO demonstrates superior environmental adaptability compared with DL under limited energy supply and collapsed infrastructure conditions. Its decentralised coordination enables nodes to cooperate locally, reducing retransmission overhead and balancing load across cluster heads. This property minimises overall energy consumption and maintains connectivity even when network topology changes unpredictably. In contrast, DL-based frameworks depend heavily on centralised computation and model inference, which require stable power and high-bandwidth connections. Even when deployed at the network edge through lightweight architectures, the cumulative energy cost remains high due to repeated updates and synchronisation.

These contrasts explain why SIO aligns better with the operational realities of disaster environments. While DL achieves high predictive accuracy in pre-disaster forecasting and post-event analysis, it lacks the agility and endurance necessary for on-site coordination once infrastructure fails. SIO, operating without pre-training or high-power hardware, sustains functionality through self-organisation and distributed intelligence. This distinction positions SIO as the more sustainable paradigm for real-time energy-aware communication in disrupted environments.

4.2 Adaptability, Scalability, and Real-Time Response

Another clear pattern emerging from the study concerns adaptability and scalability. SIO-based systems exhibit stable convergence and consistent throughput as the number of nodes increases, because each agent performs local optimisation based on residual energy and link quality. This self-organising behaviour supports real-time responsiveness, allowing the network to reconfigure immediately after node failure or interference.

By contrast, DL models require retraining or fine-tuning whenever network conditions shift. Their static parameters make them slower to respond to dynamic topology changes such as mobility or sudden link degradation. Although reinforcement or federated learning variants improve decentralisation to some extent, they still depend on continuous gradient exchange and model synchronisation, which consume additional energy and bandwidth. Consequently, SIO achieves faster adaptation with less computational and communication overhead, an essential advantage during field operations where every joule of power and second of delay matters.

4.3 Computational Burden and Deployment Feasibility

From a feasibility standpoint, SIO is computationally lightweight and can operate on low-cost embedded systems. The algorithms rely on simple arithmetic operations and short local broadcasts, enabling deployment of heterogeneous hardware such as single-board computers or sensor nodes. This makes SIO inherently portable and resilient in field conditions where device capability and connectivity vary widely.

On the other hand, DL models demand specialised processors and large memory capacity. Compressed networks such as MobileNet or TinyML variants experience performance degradation when energy supply fluctuates. In emergency conditions, where computational reliability cannot be guaranteed, DL’s dependence on hardware acceleration becomes a critical weakness. SIO avoids this constraint entirely, trading off deep abstraction for operational survivability, a trade-off that strongly favours disaster communication contexts.

4.4 Strategic Implications for Hybrid and Context-Aware Design

While SIO provides superior real-time adaptability, the analysis also shows that hybrid frameworks integrating DL and SIO can exploit the complementary strengths of both paradigms. DL-driven models excel during the anticipatory and analytical phases, for example, in hazard mapping or predictive risk estimation, where data and computation resources are abundant. SIO then dominates the reactive and recovery phases, sustaining energy-aware clustering, routing, and coordination once infrastructure is compromised.

This staged perspective implies that hybrid systems should not attempt simultaneous operation of both paradigms but rather context-adaptive switching between them. A system could employ DL components for long-term prediction and situation awareness and automatically transition to SIO-based control when communication degradation is detected. Such a context-aware mechanism aligns with the decision framework in Fig. 3, demonstrating how algorithm selection can dynamically adapt to operational constraints.

However, hybridisation introduces additional computational coupling and synchronisation overhead, which increases system complexity. Future designs should therefore prioritise modular integration with clear energy and timing thresholds to determine when the system should shift between DL-dominant and SIO-dominant modes.

4.5 Theoretical and Practical Implications

The results support the theoretical premise that disaster communication networks behave as complex adaptive systems where order emerges from decentralised interaction. Being inherently distributed, SIO aligns naturally with this paradigm, allowing local decisions to converge into global coordination without central control. DL, conversely, relies on pre-defined models that assume environmental stability, an assumption that fails under the volatile conditions of a disaster field.

Practically, these findings establish a dynamic relationship between algorithmic paradigms and the sequential phases of disaster management. During the pre-disaster stage, DL remains advantageous for predictive analytics, risk modelling, and situational awareness, where data availability and computational resources are abundant. When disaster strikes and infrastructure collapses, SIO becomes more effective by maintaining energy-aware, self-organising connectivity that supports rapid coordination among affected nodes. In the post-disaster phase, hybrid frameworks can combine DL's analytical reconstruction ability with SIO's adaptive optimisation to restore network stability and enhance recovery operations. This mapping provides an actionable guideline for system designers to select algorithms not solely based on accuracy metrics but according to environmental and temporal constraints. It also forms a theoretical bridge connecting computational intelligence with real-world disaster resilience.

5. Conclusion

This study evaluated the contextual suitability of DL and SIO in energy-aware disaster communication networks. Comparative recent findings identify how each paradigm aligns with the operational, environmental, and temporal constraints that define post-disaster communication. The analysis revealed that DL, while powerful in data-rich environments, depends heavily on computational resources and stable connectivity, making it ideal for pre-disaster prediction and post-event assessment. In contrast, SIO offers decentralised coordination, low-energy operation, and adaptive decision-making, which are essential when infrastructure collapses and nodes must self-organise to maintain connectivity. Hybrid frameworks combining both paradigms show promise by bridging predictive intelligence and real-time adaptability, though they require careful parameterisation to balance performance and complexity.

Fig. 4. Contextual Roles of Deep Learning (DL), Swarm Intelligence Optimisation (SIO), and Hybrid Paradigms Across Disaster Phases

As illustrated in Fig. 4, the three paradigms complement each other across the disaster lifecycle. DL is most effective during the pre-disaster stage when data and infrastructure are stable; SIO dominates during the disaster response phase under energy and connectivity constraints; and Hybrid frameworks support post-disaster recovery, enabling a gradual transition from reactive optimisation to predictive reconstruction.

The comparative study demonstrates that algorithm selection in disaster communication should not be driven purely by accuracy or innovation but by environmental realism. DL contributes predictive precision, SIO ensures operational survivability, and hybrid frameworks provide adaptive continuity across disaster phases. Together, they form a complementary ecosystem rather than competing technologies. This contextual interpretation departs from technology-centric evaluation toward environment-aware decision-making, enabling researchers and practitioners to match computational intelligence with real-world operational needs.

Beyond conceptual contribution, this framework provides a theoretical foundation for empirical validation. Future research will focus on simulation-based testing using realistic D2D disaster communication models. These simulations will operationalise the proposed framework by quantifying algorithmic performance, energy efficiency, adaptability, response time, and scalability under different disaster conditions. The goal is to verify the theoretical justification for paradigm selection and translate conceptual reasoning into deployable strategies for real-time emergency networks. Additionally, scenario-driven studies can further validate the framework's relevance to field operations, ensuring that algorithmic intelligence supports computational efficiency and human-centred disaster resilience.

This work contributes a perspective by reframing AI-based disaster communication as a context-driven problem rather than a purely computational one. Aligning algorithmic capability with environmental reality provides a theoretical lens for future research and a practical guideline for designing sustainable, energy-efficient, and adaptive communication systems capable of surviving when infrastructure cannot.

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References

Ahmad, R., Alhasan, W., Wazirali, R., & Aleisa, N. (2024). Optimization Algorithms for Wireless Sensor Networks Node Localization: An Overview. *IEEE Access*, *12*, 50459 – 50488. https://doi.org/10.1109/ACCESS.2024.3385487

Ahmed, S., Hossain, M. A., Chong, P. H. J., & Ray, S. K. (2024). Bio-Inspired Energy-Efficient Cluster-Based Routing Protocol for the IoT in Disaster Scenarios. *Sensors*, *24*(16), 1–20. https://doi.org/10.3390/s24165353

Alqadhi, S., Mallick, J., Alkahtani, M., Ahmad, I., Alqahtani, D., & Hang, H. T. (2024). Developing a hybrid deep learning model with explainable artificial intelligence (XAI) for enhanced landslide susceptibility modeling and management. *Natural Hazards*, *120*(4), 3719–3747. https://doi.org/10.1007/s11069-023-06357-4

Alsaaran, N., & Soudani, A. (2025). Deep Learning Image-Based Classification for Post-Earthquake Damage Level Prediction Using UAVs. *Sensors*, *25*(17). https://doi.org/10.3390/s25175406

Alshammri, G. H. (2025). Enhancing wireless sensor network lifespan and efficiency through improved cluster head selection using improved squirrel search algorithm. *Artificial Intelligence Review*, *58*(3), 1–32. https://doi.org/10.1007/s10462-024-11088-4

Antoniou, V., & Potsiou, C. (2020). A deep learning method to accelerate the disaster response process. *Remote Sensing*, *12*(3). https://doi.org/10.3390/rs12030544

Azad, M. A., Tariq, M., Sarwar, A., Sajid, I., Ahmad, S., Bakhsh, F. I., & Sayed, A. E. (2023). A Particle Swarm Optimization–Adaptive Weighted Delay Velocity-Based Fast-Converging Maximum Power Point Tracking Algorithm for Solar PV Generation System. *Sustainability (Switzerland)*, *15*(21). https://doi.org/10.3390/su152115335

Chao, M., Chenji, H., Yang, C., Stoleru, R., Nikolova, E., & Altaweel, A. (2020). EAR: Energy-aware risk-averse routing for disaster response networks. *Ad Hoc Networks*, *103*. https://doi.org/10.1016/j.adhoc.2020.102167

Cheriguene, Y., Jaafar, W., & Yanikomeroglu, H. (2025). Federated Learning in UAV-Assisted MEC Systems: A Comprehensive Survey. *IEEE Open Journal of the Communications Society*, *6*(September), 7645–7676. https://doi.org/10.1109/OJCOMS.2025.3608657

Debnath, S., Arif, W., Roy, S., Baishya, S., & Sen, D. (2022). A Comprehensive Survey of Emergency Communication Network and Management. In *Wireless Personal Communications* (Vol. 124, Issue 2). Springer US. https://doi.org/10.1007/s11277-021-09411-1

Deepak, D. C., Ladas, A., Sambo, Y. A., Pervaiz, H., Politis, C., & Imran, M. A. (2019). An Overview of Post-Disaster Emergency Communication Systems in the Future Networks. *IEEE Wireless Communications*, *26*(6), 132–139. https://doi.org/10.1109/MWC.2019.1800467

Ezugwu, A. E., Ikotun, A. M., Oyelade, O. O., Abualigah, L., Agushaka, J. O., Eke, C. I., & Akinyelu, A. A. (2022). A comprehensive survey of clustering algorithms: State-of-the-art machine learning applications, taxonomy, challenges, and future research prospects. In *Engineering Applications of Artificial Intelligence*. https://doi.org/10.1016/j.engappai.2022.104743

Gad, A. G. (2022). Particle Swarm Optimization Algorithm and Its Applications: A Systematic Review. In *Archives of Computational Methods in Engineering* (Vol. 29, Issue 5). Springer Netherlands. https://doi.org/10.1007/s11831-021-09694-4

Guleria, K., & Verma, A. K. (2019). Meta-heuristic Ant Colony Optimization Based Unequal Clustering for Wireless Sensor Network. *WIRELESS PERSONAL COMMUNICATIONS*, *105*(3), 891–911. https://doi.org/10.1007/s11277-019-06127-1

International Telecommunication Union, D. S. (2024). *Measuring digital development Facts and Figures: Focus on Landlocked Developing Countries* (Issue April).

Işık, M. F., Avcil, F., Harirchian, E., Bülbül, M. A., Hadzima-Nyarko, M., Işık, E., İzol, R., & Radu, D. (2023). A Hybrid Artificial Neural Network—Particle Swarm Optimization Algorithm Model for the Determination of Target Displacements in Mid-Rise Regular Reinforced-Concrete Buildings. *Sustainability (Switzerland)*, *15*(12). https://doi.org/10.3390/su15129715

Kyrkou, C., & Theocharides, T. (2019). Deep-learning-based aerial image classification for emergency response applications using unmanned aerial vehicles. *IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops*. https://doi.org/10.1109/CVPRW.2019.00077

Lei, C. (2024). An energy-aware cluster-based routing in the Internet of things using particle swarm optimization algorithm and fuzzy clustering. *Journal of Engineering and Applied Science*, *71*(1), 1–25. https://doi.org/10.1186/s44147-024-00464-0

Li, J., Liu, A., Han, G., Cao, S., Wang, F., & Wang, X. (2024). FedRDR: Federated Reinforcement Distillation-Based Routing Algorithm in UAV-Assisted Networks for Communication Infrastructure Failures. *Drones*, *8*(2). ttps://doi.org/10.3390/drones8020049

Li, M., & Cheng, X. (2022). Identification and Prediction of Thermodynamic Disasters During Deep Coal Mining. *International Journal of Heat and Technology*. https://doi.org/10.18280/ijht.400612

Lin, D., Peng, T., Zuo, P., & Wang, W. (2022). Deep-Reinforcement-Learning-Based Intelligent Routing Strategy for FANETs. *Symmetry*, *14*(9), 1–14. https://doi.org/10.3390/sym14091787

Manogaran, N., Raphael, M. T. M., Raja, R., Jayakumar, A. K., Nandagopal, M., Balusamy, B., & Ghinea, G. (2025). Developing a Novel Adaptive Double Deep Q-Learning-Based Routing Strategy for IoT-Based Wireless Sensor Network with Federated Learning. *Sensors*, *25*(10). https://doi.org/10.3390/s25103084

Omoniwa, B., Galkin, B., & Dusparic, I. (2022). Energy-aware optimization of UAV base stations placement via decentralized multi-agent Q-learning. *Proceedings - IEEE Consumer Communications and Networking Conference, CCNC*, 216–222. https://doi.org/10.1109/CCNC49033.2022.9700536

Rawat, P., Kumar, P., & Chauhan, S. (2023). Fuzzy logic and particle swarm optimization-based clustering protocol in wireless sensor network. *Soft Computing*. https://doi.org/10.1007/s00500-023-07833-6

Saadati, M., Mazinani, S. M., Khazaei, A. A., & Chabok, S. J. S. M. (2024). Energy efficient clustering for dense wireless sensor network by applying Graph Neural Networks with coverage metrics. *Ad Hoc Networks*, *156*(October 2023). https://doi.org/10.1016/j.adhoc.2024.103432

Saleem, M. A., Benjapolakul, W., Srisiri, W., Chaitusaney, S., & Kaewplung, P. (2025). A hybrid prediction model integrating artificial intelligence and geospatial analysis for disaster management. *IEEE Access*, *13*(March), 43716–43727. https://doi.org/10.1109/ACCESS.2025.3545449

Singh, S., Nandan, A. S., Malik, A., Kumar, N., & Barnawi, A. (2021). An Energy-Efficient Modified Metaheuristic Inspired Algorithm for Disaster Management System Using WSNs. *IEEE Sensors Journal*, *21*(13), 15398–15408. https://doi.org/10.1109/JSEN.2021.3074497

Tomar, V., Bansal, M., & Singh, P. (2023). Metaheuristic Algorithms for Optimization: A Brief Review. *Engineering Proceedings*, *59*(1), 1–16. https://doi.org/10.3390/engproc2023059238

UNDRR. (2023). *United Nations Office for Disaster Risk Reduction 2023 Annual Report*. https://www.undrr.org/annual-report/2023

Wang, L., & Jiao, H. (2024). Multi-Agent Reinforcement Learning-Based Computation Offloading for Unmanned Aerial Vehicle Post-Disaster Rescue. *Sensors*, *24*(24). https://doi.org/10.3390/s24248014

Wang, Q., Li, W., Yu, Z., Abbasi, Q., Imran, M., Ansari, S., Sambo, Y., Wu, L., Li, Q., & Zhu, T. (2023). An Overview of Emergency Communication Networks. *Remote Sensing*. https://doi.org/10.3390/rs15061595

Wang, Z., DIng, H., Li, B., Bao, L., & Yang, Z. (2020). An Energy Efficient Routing Protocol Based on Improved Artificial Bee Colony Algorithm for Wireless Sensor Networks. *IEEE Access*. https://doi.org/10.1109/ACCESS.2020.3010313

Zhang, X., Zhao, K., Gao, S., & Li, C. (2025). Optimization of Urban Fire Emergency Resource Allocation Based on Pre-Allocated Swarm Algorithm. *Fire*, *8*(1), 1–16. https://doi.org/10.3390/fire8010027