

Chapter 2

Literature Review

This chapter provides a detailed review of recent and relevant literature towards improving the performance of IoT networks using several data routing and node fault prediction methods under static and dynamic scenarios.

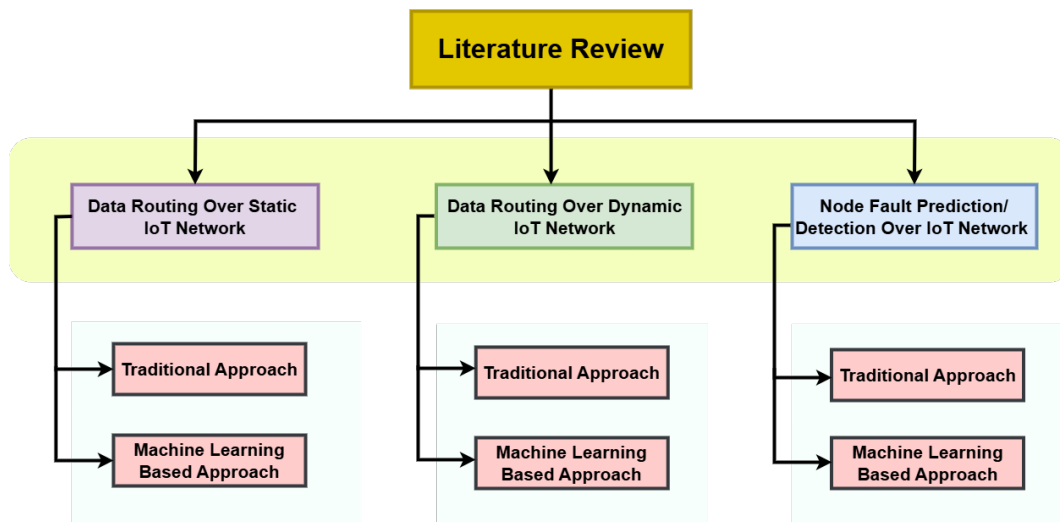


Figure 2.1: Taxonomy of literature review

The chapter has three major categories that cover all relevant state-of-the-art techniques. As shown in Figure 2.1, the three major categories of the relevant literature can be classified as, i) multi-hop data routing mechanisms over static IoT networks, ii) multi-hop data routing schemes over dynamic networks, and, iii) node fault detec-

tion/prediction frameworks over both static and dynamic networks. A more detailed discussion in the context of these approaches is provided in the following section.

2.1 Multi-hop Data Routing Over Static IoT Network

2.1.1 Traditional Approaches

Li et al., in work on particle swarm optimization (PSO) clustering [55], introduced adaptive clustering with inter-cluster routing optimization to enhance energy efficiency in WSNs. This approach improved cluster formation quality through optimized selection of cluster heads. However, the PSO-based method struggles with convergence time in larger networks and risks getting trapped in local optima. Huynh et al., in [56] developed a delay-constrained energy-efficient cluster-based routing protocol to address the single-dimensional focus on energy in previous approaches. Their method minimizes energy consumption while ensuring end-to-end delay requirements are met through delay-constrained routing combined with energy-efficient clustering. The multi-hop routing in inter-clustering transmits data packets to the base station while minimizing energy consumption. However, this approach struggles with the trade-off between delay and energy efficiency and can create cluster load overhead.

Barrachina-Muñoz et al., in [35] proposed the hybrid adaptive routing for energy efficiency (HARE) protocol stack to address the limitations of single-hop communication commonly found in low-power wide area network (LPWAN) setups. HARE enables uplink multi-hop communication whenever it is more energy-efficient than single-hop methods, achieving up to 15% energy savings without compromising network reliability. The protocol incorporates network synchronization, TDMA-like channel access, adaptive transmission power, and an energy-aware adaptive routing protocol. Despite these advantages, HARE faces increased latency issues and complexity challenges in dense network deployments. Yetgin et al.'s survey [38], comprehensively examines energy-

efficient techniques for maximizing network lifetime. They highlight the trade-offs between energy consumption and application-layer performance, advocating for cross-layer approaches to jointly optimize power allocation, link scheduling, and routing problems. Wang et al., in [57] developed an energy-efficient clustering routing algorithm specifically designed for WSN-assisted IoT environments. Their approach implements IoT-specific clustering with cross-layer optimization to improve both energy efficiency and network lifetime. However, this solution struggles with adaptation to heterogeneous IoT devices and faces scalability challenges in dense IoT deployments. Fawzy et al., in [58] introduced balanced and energy-efficient multi-hop techniques that prioritize even energy distribution across the network. Their approach optimizes multi-hop routing to achieve extended network lifetime. However, this even distribution of energy load sometimes comes at the cost of path optimality, potentially sacrificing shorter routes for better energy balance. Kim and Qiao, in [34] proposed an energy-efficient data collection method for IoT networks using cooperative multi-hop UAV networks. This innovative approach employs cooperative UAV relaying and joint optimization of UAV trajectory and data collection patterns. While achieving strong energy efficiency, this method introduces complex trajectory planning challenges and must account for UAV energy constraints. Recent innovations include adaptive ranking fuzzy-based energy-efficient opportunistic routing protocol [36], which enhances energy efficiency in IoT networks by using fuzzy logic to select volunteer nodes (VNs) based on Canberra distance, residual energy, and thresholds to assist parent nodes in data forwarding. This helps extend network lifetime and improve coverage. However, its performance declines with more VNs, and nodes near the destination-oriented directed acyclic graph root still face a high energy drain. Moreover, the assumption of supplying extra energy to some nodes may not be feasible in real deployments.

In [59], authors proposed an energy-efficient multilevel secure routing protocol that addresses energy efficiency, security, heterogeneity, and scalability in multihop IoT net-

Table 2.1: Comparison of Multi-Hop Data Routing Methods in Static IoT Networks

Paper Title	Main Approach	Key Features	Performance Metrics	Limitations
Energy-efficient routing using PSO [55]	PSO-based clustering	Adaptive clustering, Inter-cluster optimization	Energy efficiency, Cluster quality	Convergence time, Local optima
Delay-Constrained Routing [56]	Delay-aware clustering	Delay-aware routing, Energy-efficient clustering	End-to-end delay, Energy efficiency	Delay-energy trade-off, CH overhead
Multi-hop Uplink for LPWANs [35]	Multi-hop uplink	LPWAN range extension, Adaptive modulation	Coverage extension, Energy savings	Increased latency, Dense network complexity
Survey on Lifetime Maximization [38]	Survey	Comprehensive energy-efficient methods	Network lifetime, Energy use	Review only, No experimental validation
Clustering Routing for IoT [57]	IoT-WSN clustering	IoT-specific design, Cross-layer optimization	Energy savings, Lifetime improvement	Heterogeneity adaptation, Scalability
Balanced Multi-Hop Routing [58]	Load-balanced routing	Energy balancing, Multi-hop optimization	Network lifetime, Load balancing	Suboptimal paths possible
UAV-based Data Collection [34]	UAV-assisted routing	Cooperative UAV relays, Trajectory optimization	Energy savings, Data rate	UAV energy constraints, Planning complexity
Fuzzy-based Scheduling [36]	Fuzzy logic routing	Multi-criteria decision making, Adaptive schedule	Network lifetime, Energy efficiency	Overhead, Scalability limits
Secure Routing in IoT [59]	Multi-level secure routing	Security-aware design, Energy-optimized paths	Security, Energy savings	Complexity, Latency increase
Small-World UAV-IoT [60]	Delay-aware UAV routing	Small-world design, Delay control	Throughput, Delay performance	UAV positioning, Network design complexity

works. It uses a cluster-based routing approach and combines the analytic hierarchy process (AHP) with genetic algorithms to optimize inter-cluster communication. The protocol incorporates multiple trust levels—including data perception, fusion, and communication trust—to enhance security. However, its complexity may increase due to the integration of multiple algorithms, and maintaining trust calculations in large-scale dynamic environments could introduce computational overhead. To address energy imbalance, high delay, and poor throughput in large-scale multihop IoT networks, authors in [60] introduced a small-world UAV-IoT framework. By establishing optimal long-range links between device pairs, the approach ensures a low average path length and high clustering coefficient, enhancing energy efficiency and QoS. UAVs collect data from IoT devices and forward it to a ground station, significantly reducing delay and improving packet delivery ratio. However, deploying and coordinating UAVs with varying speeds, locations, and altitudes adds complexity and cost to the system, potentially

limiting its scalability in large environments. To provide a comprehensive overview of the discussed methods, a comparative analysis is presented in Table 2.1.

2.1.2 Machine Learning Based Approaches

Machine learning (ML) based approaches have gained significant traction in recent years for addressing the challenges of multi-hop data routing in IoT networks. This literature review focuses on the application of ML techniques, particularly reinforcement learning (RL), in developing efficient routing frameworks for IoT and LPWANs. The development of ML-driven routing protocols for IoT/WSN demonstrates an iterative process where every new approach addresses specific limitations of prior work while introducing new challenges. The author in [61] addresses energy efficiency and routing balance in underwater sensor networks using Q-learning. While it succeeds in reducing energy consumption and avoiding void holes, it lacks real-world validation and ignores latency and dynamic underwater behaviors. Building upon the energy-efficiency focus, [62] introduces a small world wireless sensor network (SW-WSN) model that reduces latency and balances energy better through cognitive topology adjustments. Building on QoS-aware routing, cognitive small-world network design addressed scalability limitations through hierarchical topology management. However, while it surpasses [61] in addressing latency, it too struggles with real-time adaptability and scalability in dynamic environments. The authors, in reference [63] shift to large-scale disaster management in IoT networks, proposing an energy-aware routing framework. It emphasizes realistic resource constraints, surpassing the small-world model in its application scope. Yet, like the previous two, it falls short due to reliance solely on simulations and insufficient attention to reliability and overhead. To tackle robustness, the authors in [64] proposed an AI-based robust topology model for smart city IoT networks. It strengthens resilience against attacks and reduces computational cost, filling the security void. However, it doesn't address data routing, latency, or adaptability, creating a gap in communication

efficiency. Whereas, the authors in [65] developed a Q-learning approach for LPWAN optimization that reduced computational complexity through decentralized learning agents. While their method achieved 92% QoS compliance in smart city scenarios,

Table 2.2: Comparative analysis of ML-based routing protocols in Static IoT networks

Paper Title	ML Approach	Key Features	Performance Metrics	Limitations
QL-EEBDG for Underwater Networks [61]	Q-Learning	Void hole avoidance, Energy balancing	Energy tax, Network stability period	Slow convergence in 3D underwater environments
Low-Latency Energy-Balanced Transmission [62]	Small World Optimization	Cognitive small-world networks, Energy balancing	Latency, Energy consumption	Performance dependent on network density
Cognitive Routing Protocol for Disaster-Inspired IoT [63]	Cognitive Hierarchy Theory	Dynamic path selection, Risk-aware routing	Packet delivery ratio, Energy consumption	High computational overhead in large networks
Intelligent Robust Networking Mechanism [64]	Deep Reinforcement Learning	Topology robustness, Self-healing networks	Network robustness, Convergence time	High training overhead for DRL model
Improving Energy Efficiency and QoS of LPWANs Using Q-Learning [65]	Q-Learning	QoS-aware routing, Energy balancing	Energy efficiency, Network latency	Initial latency overhead during Q-table convergence
Energy-Efficient Intelligent Routing Scheme [66]	Neuro-Fuzzy System	Fuzzy logic-based clustering, Neural network routing	Network lifetime, Energy efficiency	High computational complexity
NM-LEACH Protocol [67]	Modified LEACH with Clustering	Energy-aware cluster head selection	Network lifecycle, Energy balance	Limited adaptability in dynamic environments

it required extensive training datasets and struggled with network scalability beyond 200-node clusters. By introducing a Q-learning-based multi-hop routing method for LPWANs, offering energy efficiency, better QoS, and scalability. It outperforms earlier methods in large-scale IoT deployments, especially in connectivity. However, its static deployment focus limits its applicability to mobile or dynamic scenarios, a critical need in modern IoT systems. To address data heterogeneity and dynamic load, the author in reference [66] proposes a DRL-based routing algorithm for IoT-WSNs, considering multi-objective metrics like delay, throughput, and load for both intra- and inter-cluster routing. It improves upon the limitations of fixed Q-learning strategies in LPWANs. Still, it remains confined to simulations and lacks built-in fault tolerance or real-time congestion handling. Their intelligent cluster head selection mechanism effectively managed heterogeneous node capabilities but required 128 MB memory allocation per base

station for RL model operation - a significant constraint for resource-constrained edge devices. Finally, [67] presents novel modified low-energy adaptive clustering hierarchy (NM-LEACH), a refined LEACH protocol, targeting energy imbalance and inefficient cluster head (CH) selection by incorporating residual energy and distance factors. While it provides a structured and lightweight solution compared to DRL models, it doesn't address complex metrics like delay or network dynamics, nor does it handle modern security or scheduling concerns. To provide a comprehensive overview of the discussed methods, a comparative analysis is presented in Table 2.2.

2.2 Multi-hop Data Routing Over Dynamic IoT Network

2.2.1 Traditional Approaches

The rapid growth of IoT devices has led to new and difficult challenges in data routing, particularly in dynamic environments where network topology changes over time. Multi-hop data routing in time-varying IoT networks has emerged as a critical research area to address issues related to energy efficiency, reliability, coverage extension, and QoS. This literature review synthesizes recent advances in this domain, focusing on emerging approaches and technologies that enable efficient data routing in dynamic IoT ecosystems. For clarity, the traditional approach has been segmented into three distinct parts.

Low Power Wide Area Networks and Multi-hop Communication: LP-WANs form the backbone of many IoT deployments, offering long-range communication with minimal energy consumption. The authors in [68] provide a comprehensive survey of LPWAN technologies, highlighting the limitations of single-hop architectures in terms of coverage, reliability, and energy efficiency. The author identifies multi-hop communication as a potential solution to extend network coverage and optimize energy consumption, particularly in dense urban environments. Building on this foundation,

authors in [35] specifically investigate multi-hop communication in the uplink for LP-WANs. Their work demonstrates that multi-hop topologies can significantly extend network coverage by up to 200% compared to single-hop approaches while reducing transmission energy at end devices. However, they also highlight challenges related to relay selection and coordination, which become particularly acute in time-varying networks where nodes may join or leave unpredictably. Lalle et al., in [69] extended this analysis to LoRaWAN networks, providing a comprehensive survey of routing strategies and proposing a software-defined networking (SDN) based solution for smart water grids. Their work emphasizes the need for adaptive routing protocols that can respond to changing network conditions, a critical requirement in time-varying IoT deployments. The authors identify scalability and reliability as key challenges, noting that traditional routing approaches often fail to accommodate the dynamic nature of IoT networks.

Energy-Efficient Routing Approaches: Energy efficiency remains a primary concern in IoT networks due to the battery-constrained nature of many devices. Anedda et al., in [70] proposed an energy-efficient solution for multi-hop communications in LP-WANs, introducing a cooperative relaying scheme that optimizes power consumption by selecting relays based on link quality and residual energy. Whereas, Paul et al., in [42] introduced a novel energy-efficient routing scheme specifically designed for LoRa networks. The proposed approach leverages network-wide energy awareness to balance load across nodes and extend network lifetime. Similarly, Effah et al., in [71] focused on agricultural IoT applications, proposing an energy-efficient multihop routing framework for cluster-based systems. Their approach optimizes both intra-cluster and inter-cluster communication, achieving a 30% improvement in network lifetime compared to traditional protocols. This specialized approach highlights the importance of domain-specific optimizations in IoT routing. Diakhate et al., in [72] take a more classical approach, optimizing energy consumption using Dijkstra's algorithm for route selection. Their work demonstrates that even traditional routing algorithms can be effectively adapted

for IoT environments with appropriate energy-aware cost functions. However, their approach lacks the adaptability needed for highly dynamic networks where topology changes frequently.

Table 2.3: Comparative Analysis of Multi-Hop Data Routing Approaches in Time-Varying IoT Networks

Paper Title	Main Approach	Key Features	Performance Metrics	Limitations
Low power wide area networks: A survey of enabling technologies, applications and interoperability needs [68]	LPWAN Survey	Reviews LPWAN technologies; Identifies single-hop limitations	Coverage analysis; Energy efficiency	Theoretical only; No new routing protocol proposed
Multi-hop communication in the uplink for LPWANs [35]	Multi-hop Communication	Multi-hop uplink for LPWANs; Relay selection and coordination	Coverage extension; Reduced end-device energy usage	Relay coordination complexity; Unpredictable node dynamics
Routing Strategies for LoRaWAN Multi-Hop Networks: A Survey and an SDN-Based Solution for Smart Water Grid [69]	SDN-based for LoRaWAN	Adaptive routing for smart water grids; SDN integration	Scalability; Reliability in dynamic networks	Limited to LoRaWAN; Requires centralized control
An energy-efficient solution for multi-hop communications in low power wide area networks [70]	Cooperative Relaying in LPWAN	Relay selection using link quality and residual energy	Reduction in energy consumption	Static networks; No support for mobility
A novel energy-efficient routing scheme for LoRa networks [42]	Energy-Aware Routing for LoRa	Network-wide energy balancing; Load distribution	Improvement in network lifetime	LoRa-specific; Limited topology adaptability
Energy-Efficient Multihop Routing Framework for Cluster-based Agricultural IoT [71]	Cluster-Based Optimization (Agri-IoT)	Intra/inter-cluster optimization; Domain-specific design	Increase in network lifetime	Agriculture-specific; Scalability concerns
Optimizing The Energy Consumption of WSN by Using Energy Efficient Routing Protocol Using Dijkstra Algorithm [72]	Classical Algorithm Adaptation	Energy-aware Dijkstra's algorithm for route selection	Optimized energy consumption	High overhead; Poor adaptability in dynamic topologies
Energy-efficient data collection and device positioning in UAV-assisted IoT [40]	UAV-Assisted IoT Routing	UAV trajectory scheduling; Efficient data collection	Energy savings; High data collection rate	UAV mobility and battery constraints
Resilient Edge: Building an adaptive and resilient multi-communication network for IoT Edge using LPWAN and WiFi [73]	Adaptive Multi-Communication	Dynamic LPWAN/WiFi selection; Edge computing support	Reliability improvement	Edge resource constraints; Complex tech selection

UAV-Assisted and Heterogeneous Network Routing: UAVs have emerged as a promising technology to enhance IoT network coverage and flexibility. The au-

thors in [40] investigate energy-efficient data collection and device positioning in UAV-assisted IoT, proposing a framework that optimizes UAV trajectory and communication scheduling. Their approach reduces energy consumption by 25% while maintaining high data collection rates. Kumar et al. [73] propose Resilient Edge, an adaptive multi-communication network for IoT edge using LPWAN and WiFi. Their framework dynamically selects the optimal communication technology based on network conditions and application requirements, demonstrating a 45% improvement in reliability in dynamic environments. This hybrid approach illustrates the potential of combining multiple communication technologies to enhance routing performance in time-varying networks.

Mobility Management in Time-Varying IoT Networks: Mobility management represents a significant challenge in time-varying IoT networks where nodes may move, join, or leave the network dynamically. The authors in [74] propose MSE-RPL, a mobility support enhancement for the RPL routing protocol widely used in IoT applications. Their approach introduces mobility prediction and preemptive handover mechanisms, reducing packet loss by 45% in mobile scenarios compared to standard RPL. In reference [75], the authors present EGRPM, an energy-efficient geographic routing protocol based on the mobile sink in wireless sensor networks. Their approach optimizes routing paths to mobile data collection points, reducing energy consumption by 38% while maintaining high delivery ratios. This work highlights the potential of mobile sinks to enhance routing efficiency in dynamic IoT deployments. Reference [76] addresses time-critical applications with their VANET multi-hop routing method, designed specifically for vehicular IoT. Their approach incorporates real-time traffic information and vehicle movement patterns to optimize routing decisions, reducing end-to-end delay by 40% in highly dynamic scenarios. To tackle the challenge of vertical handover in heterogeneous LPWANs, authors in [77] propose an efficient mechanism to transfer connections between different communication technologies. Their approach

reduces handover latency by 60% compared to traditional methods, enabling seamless connectivity in dynamic multi-technology environments.

Despite significant advances in multi-hop data routing for time-varying IoT networks, several important research gaps remain. Most existing approaches focus on specific aspects of the routing problem, such as energy efficiency or mobility management, without addressing the holistic requirements of dynamic IoT environments. Future research should aim to develop integrated solutions that simultaneously optimize multiple performance metrics while adapting to time-varying network conditions. To provide a comprehensive overview of the discussed methods, a comparative analysis is presented in Table 2.3.

2.2.2 Machine Learning Based Approaches

Machine learning approaches have gained significant traction in IoT routing due to their ability to adapt to changing network conditions. The authors in [65] introduce a Q-learning based data routing method to improve energy efficiency and QoS in LPWANs. Their approach learns optimal forwarding decisions over time, achieving an increase in network lifetime and improvement in packet delivery ratio compared to traditional approaches. Along with this, authors in [78] propose a similarity-enhanced ϵ -greedy algorithm for learning optimal routing in the uplink for LPWANs. Their method leverages historical data to make informed routing decisions, reducing exploration overhead by 40% compared to standard reinforcement learning approaches. Building on this work, authors in [79] present a more comprehensive learning-based multi-hop routing framework that balances energy consumption and reliability, achieving near-optimal performance after a relatively short learning period. In this work, the authors demonstrate that selecting an optimal path for multi-hop communication that enables energy-efficient data transmission is a crucial problem. Subsequently, the authors propose an epsilon multi-hop RML-based method that utilizes the epsilon-greedy model for reliable

and low-power consumption data transmission over LPWAN. In reference [41], the authors introduce an energy-efficient SDN controller architecture with blockchain-based security for IoT networks. Their approach centralizes routing decisions while maintaining distributed security, demonstrating a 30% reduction in energy consumption and enhanced protection against routing attacks. This work highlights the importance of addressing security concerns alongside performance optimization in IoT routing protocols. In reference [80], authors explore cognitive radio (CR) technologies for LPWANs, proposing intelligent spectrum management to enhance routing performance in congested environments. Their approach dynamically selects optimal frequency bands for transmission, improving both reliability and energy efficiency in interference-prone scenarios. In recent years, the advancement of machine learning techniques has led the way to provide solutions to the most critical problems that are difficult to analyze empirically. Specifically, there is an increase in the popularity of reinforcement machine learning (RML) based solutions due to its ability to provide a framework through which the system can learn and adapt from its previous exchange with the underlying environment [81]. A deep-RML framework for data routing is proposed in [82]. The states of the nodes are represented as link-utilization levels, and the action space represents how the routing policy is changing within the network. However, the network architecture is centralized in [82], which increases the computational load on the central server. For instance, an RML-based congestion avoidance routing in the underwater acoustic sensor networks is proposed in [83]. The method proposed in [83] traverses hop-by-hop from source node to destination node, keeping data transmission delay and energy consumption as a reward function. On the contrary, in this work, the optimal number of hops required to reach the destination node is computed. This ensures delay minimization. Eventually, in [84], a cognitive LPWAN architecture has been developed for efficient communication over a hybrid LPWAN. In this work, an AI-enabled hybrid framework is proposed to fulfill the demand of diverse IoD. Recently,

Table 2.4: Comparative Analysis of Machine Learning-Based IoT Routing Approaches

Title	Method	Key Contribution	Performance Metrics	Limitations
Improving energy efficiency and QoS of LPWANs for IoT using Q-learning based data routing [65]	Q-learning-based data routing	Adaptive energy efficiency & QoS improvement in LPWANs	Increase in network lifetime, improvement in packet delivery ratio	Requires training data, computational overhead
Learning optimal routing for the uplink in LPWANs using similarity-enhanced ϵ -greedy [78]	Similarity-enhanced ϵ -greedy algorithm	Reduction in exploration overhead compared to standard RL	Faster convergence in routing decisions	Limited to uplink scenarios
Towards energy efficient LPWANs through learning-based multi-hop routing [79]	ϵ multi-hop RML framework	Balances energy-reliability tradeoff in multi-hop routing	Near-optimal performance after short learning period	Initial learning phase impacts early performance
An energy-efficient SDN controller architecture for IoT networks with blockchain-based security [41]	SDN + Blockchain architecture	Centralized routing with decentralized security	Reduction in energy consumption, enhanced protection against routing attacks	Central server load, scalability concerns
CR-LPWAN: Issues, solutions and research directions [80]	Cognitive radio spectrum management	Dynamic frequency selection in congested environments	Improved reliability and energy efficiency in interference-prone scenarios	Hardware complexity, spectrum sensing challenges
Reinforcement learning based routing in networks: Review and classification of approaches [81]	Deep-RML (link-utilization states, centralized control)	Adaptive routing policy optimization	Not explicitly quantified	High central server computational load
RCAR: A Reinforcement-Learning-Based Routing Protocol for Congestion-Avoided Underwater Acoustic Sensor Networks [83]	Hop-by-hop RML with delay/energy rewards	Optimized hop count for underwater networks	Reduced transmission delay	Environment-specific (not generalizable)
Cognitive-LPWAN: Towards intelligent wireless services in hybrid low power wide area networks [84]	AI-enabled hybrid LPWAN framework	Supports diverse IoT device requirements	Efficient hybrid communication	Integration complexity across technologies
On the feasibility of mobile sensing and tracking applications based on LPWAN [85]	LoRaWAN mobility evaluation	Validated low-speed device support	Practical performance metrics for mobile scenarios	Limited to ≤ 30 km/h mobility
On the mobile communication requirements for the demand-side management of electric vehicles [86]	LPWAN for EV communication	Mobile urban data exchange solution	Efficient throughput for EV networks	Urban-environment specific

intelligent and efficient data transfer over dynamic LPWAN has received more attention among the research community with respect to time-varying IoT networks [87]. The mobility-aware LPWAN protocols are the key to enhancing the performance of time-varying IoT networks. The authors in [85] evaluate the performance of real-world LoRaWAN applications over a wide geographical area under node mobility conditions. The paper investigates the capability of LoRaWAN to cope with low-speed device applications. In addition, the authors in [86] propose the use of an LPWAN solution for mobile communication among electric vehicles (EVs) in urban environments. Furthermore, the authors validate that the proposed LPWAN technology is capable of handling an adequate amount of information, resulting in efficient data throughput. Machine learning approaches show great promise but require substantial training data and computational resources, limiting their applicability in resource-constrained IoT devices. Developing lightweight, distributed learning algorithms that can operate with minimal overhead is an important direction for future research. Additionally, the integration of heterogeneous communication technologies remains challenging, with most existing approaches focusing on single-technology solutions. Future work should explore unified routing frameworks that seamlessly operate across different network tiers and communication standards, enabling truly ubiquitous IoT connectivity. Multi-hop data routing in time-varying IoT networks presents unique challenges that require innovative solutions beyond traditional networking approaches. This literature review has synthesized recent advances in energy-efficient routing, UAV-assisted networking, learning-based approaches, mobility management, and specialized solutions for specific IoT scenarios. The field is rapidly evolving, with increasing focus on adaptive, intelligent routing protocols that can respond to the dynamic nature of IoT deployments. While significant progress has been made, substantial research opportunities remain in developing integrated, secure, and efficient routing solutions that can operate effectively in the complex, time-varying environments characteristic of modern IoT applications.

To provide a comprehensive overview of the discussed methods, a comparative analysis is presented in Table 2.4.

2.3 Node Fault Detection/Prediction Over IoT Network

The reliability and efficiency of IoT networks depend significantly on the ability to detect and predict node faults, which can arise due to hardware failures, software errors, or environmental factors. This literature review focuses on recent advancements in node fault detection and prediction techniques for IoT networks, highlighting both traditional and machine learning-based approaches.

2.3.1 Traditional Fault Detection Approaches

Anomaly detection approaches based on cumulative summation (CUSUM), data clustering, data density, and support vector machine (SVM) are demonstrated in [88]. It lists and compares the advantages of each of the methods discussed. The authors in [89] proposed a distributed fault detection algorithm that detects faulty nodes based on a weighted average value scheme. In [89], the data of a node is compared to the weighted average data of its neighboring nodes for fault detection with low false alarm rates. On the other hand, to perform more accurate recovery actions, the authors in [90] focused on the identification and classification of data and system fault types. In this method, hidden markov models (HMMs) are used to capture fault-free dynamics of an environment and dynamics of faulty data, over which a structural analysis is performed to determine the type of data and system faults affecting sensor measurements. To deal with the situation of densely populated WSN, the authors in [91] proposed a new distributed bayesian algorithm (DBA). DBA technique gives much better fault detection accuracy over traditional distributed fault detection (DFD) in cases with a large number of faulty nodes. For fault detection in real-time, the authors in [92] proposed a new distributed fault detection algorithm based on the temporal and spatial correlation of data collected

by sensor nodes. The proposed algorithm is used to detect and discard faulty data locally, hence minimizing network resource consumption. The authors in [93] proposed an SVM classification-based fault detection scheme. Based on SVM, a decision function is defined that is a light process in terms of resource requirements. Hence, it can be easily executed at cluster heads to detect anomalous sensors. To have a high network cohesion, the authors in [94] proposed a new DFD method to identify nodes that have high local importance to keep these nodes in the network for a long time. The authors in [95] presented a distributed fault-tolerant mechanism called cluster member based fault tolerant (CMATO) for WSN. Here, individual clusters are perceived as a whole. Therefore, it quickly detects and recovers the fault. CMATO increases the robustness of the network as it can deal with multiple CH failures. In [96], the authors suggested a novel energy-aware fault tolerance scheme called informer homed routing (IHR) which significantly reduces energy consumption compared to LEACH and dual homed routing (DHR). In [97], the authors developed a fault-tolerance method using fuzzy logic strategy. Here, the authors designed a fault detection, isolation, and recovery model and demonstrated the use of the model in identifying faulty nodes. In [98], the authors proposed a regular hexagonal based clustering scheme (RHCS) and a scale free topology evolution mechanism (SFTEM) for WSNs. RHCS, along with SFTEM, provides fault tolerance and improves network robustness. For fault-tolerance in IoT-enabled WSN, in [99] a DRL-based maximum coverage location problem (MCLP) algorithm is proposed. It helps to find the optimal location for CH placement. In [100], based on the kernel function, a fault prediction method is proposed by the authors, which is used to evaluate the performance of Ribbon WSN. An evidential reasoning (ER) and belief-rule-based (BRB) methods are proposed in [101] for fault prediction in WSN. In [102], the authors proposed an auto-regressive integrated moving average (ARIMA) model, which could predict anomalies by the technique of time-series forecasting.

2.3.2 Machine Learning-Based Fault Detection

Detecting node faults in IoT networks presents significant challenges due to environmental constraints, as well as energy and resource limitations. Various approaches have been explored to address this issue. A neural network-based fault diagnosis protocol [49] utilizes a particle swarm optimization-based fuzzy multilayer perceptron to handle multiple fault types. However, it relies on predefined models or assumptions. An energy-efficient fault diagnosis technique [51] is proposed using feed-forward neural networks, enabling sensor nodes to independently detect their fault status. However, the technique imposes high computational demands on sensor nodes and lacks the ability to detect complex faults. The authors in [103] used a fuzzy CNN for fault prediction in heterogeneous IoT environments. The model achieves high accuracy with data fusion but may struggle with generalization across different sensor types. Further, [104] proposed a Kalman filter-based method for sensor fault detection, emphasizing computational efficiency and eliminating the need for training data. However, its centralized processing architecture introduces scalability challenges while validation is limited to abrupt faults, leaving intermittent faults unaddressed. In [105], authors proposed an energy-efficient clustering and routing protocol using an adaptive shark smell optimization (ASSO) algorithm and a modified Elman recurrent neural network for fault prediction in WSNs. While effective in improving energy efficiency and accuracy, the model is computationally complex and lacks real-world deployment analysis.

For vehicular networks, [52] proposes the semi-gated recurrent unit method for anomaly detection, combining data oversampling with semi-supervised learning to improve detection accuracy. However, the use of oversampling may introduce synthetic noise, potentially affecting detection accuracy. In conclusion, while these methods offer significant advancements in fault detection and network performance, they each face limitations such as dependency on predefined models, scalability issues, reliance on assumptions, or the risk of noise, which must be carefully addressed for broader

applicability.

2.4 Small-World Phenomenon in IoT Network

The small-world phenomenon, characterized by a high clustering coefficient and a low average path length, has been increasingly applied to IoT networks to enhance their efficiency and robustness. The author in [106] explores the application of small-world and scale-free network models in IoT systems. These models are crucial for understanding and optimizing the topology of IoT networks, which involve a massive number of interconnected devices. The paper highlights how small-world networks can improve synchronization and error tolerance in IoT systems by reducing the average path length between nodes, thus enhancing network efficiency and reducing latency. A recent study published in Nature [107] provides new insights into the structure of small-world networks. It emphasizes the importance of clusters linked by shortcuts in achieving small-world properties, rather than just focusing on the mean number of shortcuts. This work offers a more precise characterization of small-world networks and could be applied to IoT networks to optimize their performance by identifying key clusters and shortcuts that enhance connectivity. Small-world networks are generally characterized by a high clustering coefficient and a short average path length, which allows for efficient information transfer and robustness against failures. These properties make them suitable for IoT networks, where devices need to communicate efficiently while maintaining low energy consumption.

The application of the small-world phenomenon in IoT networks offers several advantages, such as efficient data transmission, energy efficiency, and robustness. However, integrating small-world properties into IoT networks poses challenges, such as maintaining a balance between clustering and path length, and ensuring scalability with the increasing number of devices. Future research should focus on developing novel routing strategies and node placement algorithms that leverage small-world characteristics to

enhance IoT network performance.

2.4.1 Summary

Recent literature on multi-hop data routing in time-varying IoT networks highlights significant advancements in energy-efficient, adaptive, and reliable communication strategies. Studies emphasize the limitations of traditional single-hop and static routing, advocating for multi-hop, SDN-based, and hybrid solutions—often leveraging LPWANs, UAVs, and edge computing—to enhance coverage, scalability, and robustness. Machine learning and fault prediction techniques are increasingly integrated to proactively manage node failures and improve QoS. However, challenges remain in relay coordination, adaptability to dynamic topologies, and balancing computational overhead with network performance. Overall, the field is moving toward intelligent, context-aware routing frameworks that can dynamically respond to the evolving demands of large-scale, heterogeneous IoT environments