Chapter 7

Conclusions and Future Directions

This chapter concludes the thesis and provides the possible future research directions. The conclusions and future works in detail are discussed as follows.

7.1 Conclusions

In conclusion, this thesis focused on solving key problems in IoT networks like efficient data routing, energy saving, and predicting node failures. New methods using machine learning and reinforcement learning were developed for both static and dynamic networks. These approaches helped improve network performance, reduce delays, and increase reliability. The results were tested in both simulations and real-world setups, proving their usefulness. The detailed conclusions of this thesis is discussed below.

- **Addressing IoT Challenges**: This thesis has successfully addressed critical challenges faced by IoT networks, particularly in terms of data routing, energy efficiency, node fault prediction, and network reliability in both static and dynamic environments.
- **Joint Node Fault Prediction and Data Routing:** A novel approach is developed for node fault prediction using an unsupervised local outlier factor (LOF) method combined with a Q-learning framework for optimal data routing in static

IoT networks. The proposed method achieves a throughput ratio of over 95% on the simulated IoT testbed and over 90% on the real-field dataset, significantly outperforming existing methods such as Q-learning (70% and <75%), LEACH (82% and <80%), and BEEMH (58% and <70%). It also reduces average data latency to less than 8 s on the simulated testbed and 5.8 s on the real-field dataset, compared to QL-EEBDG (12.2 s) and Q-learning (9.8 s). In terms of energy efficiency, the proposed method maintains a network lifetime above 90% up to 1500 iterations (simulated) and 92% up to 1750 iterations (real-field), with residual energy improvements of up to 30% over LEACH and 27.5% over K-means++. Energy consumption is also more evenly balanced across nodes, as indicated by a lower standard deviation compared to LEACH, K-means++, and NM-LEACH. This approach minimizes the impact of faulty nodes and ensures efficient data transmission.

- **Dynamic IoT Network Routing:** A reinforcement learning based data routing algorithm, OptRISQL, was introduced for dynamic, time-varying IoT networks. This algorithm dynamically selects optimal relay nodes at discrete time instants, improving network longevity, energy efficiency, and QoS. In simulated environments, the proposed method reduced the proportion of inoperative IoDs to 53% after 200 snapshots, compared to LMHR (60%), DT (98.25%), and CR (99%). On the real-field dataset, only 46% of IoDs became inoperative at 200 snapshots, versus LMHR (67%), RG (94.75%), and DT (98%). Moreover, data throughput improved significantly, with 216 packets delivered to the gateway at 200 snapshots in real-field tests, compared to only 61% of that amount for LMHR, 9% for RG, 2.8% for DT, and 1.4% for CR. The proposed method also achieved a low average data latency of 0.6322 s in the real-field dataset, compared to CR (7.2308 s) and LMHR (over 2.76 s), while maintaining more active nodes and avoiding early network deterioration. Data interference was also reduced, with up to 45.5% fewer

IoDs experiencing high interference in simulations, and 42% fewer in real-field scenarios.

- **Energy-Efficient and QoS-Aware Framework:** An energy-efficient, QoS-aware data routing framework was proposed, incorporating LSTM-based deep learning for accurate fault prediction and actor-critic reinforcement learning for adaptive routing. The proposed fault prediction model achieved perfect accuracy (1.0) on simulated and real-field datasets, F1-scores above 0.9 under all conditions, and clearly outperformed RF, Fuzzy, LOF, and K-means methods. In terms of QoS, the method achieved a throughput ratio of 85% on the simulated IoT testbed and 82% on the real-field dataset after 2000 iterations, compared to ACR (50% and 65%), ABR (52% and 62%), CRPD (38% and 53%), DDR (17% and 10%), and E-FEERP (7% and 4%). The average data latency was reduced to 1.1 s (simulated) and 0.7 s (real-field), lower than DDR and E-FEERP, and comparable to ACR and CRPD while maintaining higher fault tolerance. Energy efficiency analysis showed a network lifetime of 92% (simulated) after 2000 iterations, outperforming ABR, CRPD, DDR, and E-FEERP. The method also maintained the lowest standard deviation of energy consumption across nodes in both simulated and real-field scenarios, indicating highly balanced energy usage compared to existing approaches.
- **Small-World Characteristics in IoT Networks:** The integration of small-world characteristics with strategically placed long-range links was evaluated to reduce latency, improve connectivity, and enhance scalability. Using soft actor critic with node fault prediction (SAC-NFP), the method achieved high fault prediction performance with DBSCAN. For example, accuracy and precision above 90%, and F1-scores exceeding 90% at high fault noise levels outperform LOF, isolation forest, elliptic envelope, and one-class SVM. In routing performance, SAC-NFP achieved 22,000 bps throughput, 0.090 s latency, and improved net-

work lifetime, surpassing PPO, Q-learning, and conventional multi-hop routing. It also maintained higher data delivery across varying initial energy levels, confirming the benefits of long-range links in small-world networks for sustaining high throughput, low latency, and extended lifetime.

- **Practical Validation:** The proposed methodologies were validated using both simulated and real-field IoT testbeds, demonstrating their applicability and effectiveness in real-world, large-scale IoT applications.

7.2 Future Works

The following directions are identified for future work to enhance IoT network performance and intelligence. These include integrating small world characteristics, employing advanced machine learning techniques, and leveraging edge computing and federated learning for improved efficiency, security, and scalability.

- **Integration of Small-World Characteristics (SWC) in Dynamic IoT Networks:** In this work, SWC was introduced in static IoT networks to improve efficiency and reduce communication overhead. Future work will focus on extending this approach to dynamic IoT networks, where node mobility and time-varying topologies pose additional challenges for maintaining long-range links and ensuring reliable communication.
- **Utilizing Machine Learning Frameworks for SWC:** ML-based frameworks (including actor–critic reinforcement learning) are used in this thesis to optimize SWC in static settings. As a continuation, future work will investigate advanced ML methods such as deep RL and federated learning to adaptively manage SWC in dynamic IoT networks. This would improve scalability and real-time adaptability in practical deployments.
- **Joint Node Fault Prediction and Data Routing in Small World IoT Networks:** We will investigate algorithms that simultaneously predict node faults

and optimize data routing paths to ensure robust performance in Small World IoT networks.

- **Sophisticated Multi-Hop Data Routing Scheme with Graph Convolutional Neural Networks (GCNN):** We aim to develop an advanced multi-hop routing scheme using graph convolutional neural networks (GCNN) to improve routing decisions in time-varying IoT networks.
- **Interference-Aware Protocols for Dense IoT Networks:** Research will focus on interference-aware protocols to manage dense, time-varying IoT networks, ensuring robust performance under high communication traffic and dynamic conditions.
- **Federated Learning and Edge Computing for Robust Security:** Future work will investigate federated learning and edge computing for developing secure, privacy-preserving models to enhance real-time decision-making and resilience in IoT networks.
- **Integration of Edge Computing for Computation Offloading:** The integration of edge computing will be explored to offload complex computations from resource-constrained IoT devices, improving efficiency and reducing latency.