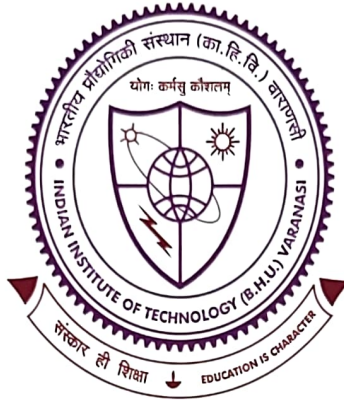


Intelligent Node Fault Prediction and Route Optimization Mechanisms for IoT Networks



Thesis submitted in partial fulfillment
for the award of degree of

Doctor of Philosophy

By

Neha Sharma

Department of Electronics Engineering
INDIAN INSTITUTE OF TECHNOLOGY
(BANARAS HINDU UNIVERSITY)
VARANASI - 221005
INDIA

Roll No. 22091004

Year 2025

CERTIFICATE

It is certified that the work contained in the thesis titled "*Intelligent Node Fault Prediction and Route Optimization Mechanisms for IoT Networks*" by *Neha Sharma* has been carried out under my supervision and this work has not been submitted elsewhere for a degree. It is further certified that the student has fulfilled all requirements of Comprehensive Examination, Candidacy, and SOTA for the award of Ph.D. Degree.

Date of Submission: 21/08/2025

Om Jee Pandey
21/08/25
Supervisor

Dr. Om Jee Pandey
Assistant Professor

Department of Electronics Engineering
Indian Institute of Technology (BHU) Varanasi

सहायक आचार्य/Assistant Professor
इलेक्ट्रॉनिकी अभियांत्रिकी विभाग
Department of Electronics Engineering
भारतीय प्रौद्योगिकी संस्थान
Indian Institute of Technology
(बनारस हिन्दू यूनिवर्सिटी)
(Banaras Hindu University)
वाराणसी/Varanasi-221005

DECLARATION BY THE CANDIDATE

I, **Neha Sharma**, certify that the work embodied in this Ph.D. thesis is my own bonafide work carried out by me under the supervision of **Dr. Om Jee Pandey** from **July-2022** to **May-2025** at **Department of Electronics Engineering**, Indian Institute of Technology (BHU) Varanasi. The matter embodied in this thesis has not been submitted for any other degree/diploma award. I declare that I have faithfully acknowledged and given credits to the research workers wherever their works have been cited in my work in this thesis. I further declare that I have not willfully copied any other's work, paragraphs, text, data, results, *etc.*, reported in journals, books, magazines, reports, dissertations, theses, *etc.*, or available at websites and have not included them in this thesis and have not cited as my own work.

Date: 21/08/2025

Place: Varanasi



Neha Sharma

CERTIFICATE BY THE SUPERVISOR

This is to certify that the above statement made by the candidate is correct to the best of my knowledge.



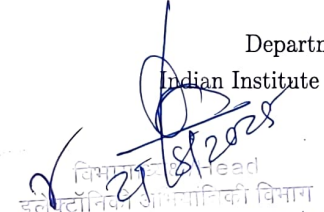
21/08/25
Dr. Om Jee Pandey

Assistant Professor

Department of Electronics Engineering

Indian Institute of Technology (BHU) Varanasi

Signature of Head of the Department



विभागाध्यक्ष/Head
इलेक्ट्रॉनिक्स अभियांत्रिकी विभाग
Department of Electronics Engineering
भारतीय प्रौद्योगिकी संस्थान
Indian Institute of Technology
(बनारस हिन्दू यूनिवर्सिटी)
(Banaras Hindu University)
वाराणसी/Varanasi-221005

सहायक आचार्य/Assistant Professor
इलेक्ट्रॉनिक्स अभियांत्रिकी विभाग
Department of Electronics Engineering
भारतीय प्रौद्योगिकी संस्थान
Indian Institute of Technology
(बनारस हिन्दू यूनिवर्सिटी)
(Banaras Hindu University)
वाराणसी/Varanasi-221005

COPYRIGHT TRANSFER CERTIFICATE

Title of the Thesis: Intelligent Node Fault Prediction and Route Optimization Mechanisms for IoT Networks


Name of the Student: Neha Sharma

Copyright Transfer

The undersigned hereby assigns to the Indian Institute of Technology (Banaras Hindu University) Varanasi all rights under copyright that may exist in and for the above thesis submitted for the award of the *Doctor of Philosophy*.

Date: 21/08/2025

Place: Varanasi


Neha Sharma

Note: However, the author may reproduce or authorize others to reproduce material extracted verbatim from the thesis or derivative of the thesis for author's personal use provided that the source and the Institute's copyright notice are indicated.

Dedicated to
Baba Vishwanath, Maa Annapurna,
Mother Nature and my beloved Husband


ACKNOWLEDGEMENT

I extend my sincere appreciation to all who have, in various ways, contributed to the completion of this Ph.D. thesis. This journey would not have been possible without the unwavering support and encouragement I received along the way. First and foremost, I extend my heartfelt thanks to Baba Vishwanath and Mata Annapurna, whose divine blessings, strength, and wisdom have continually inspired and guided me throughout this academic endeavor. I also bow my head in reverence to Kaal Bhairav, the Kotwal of Kashi, whose grace has preserved my health and well-being during these formative years. With deep respect, I pay homage to Bharat Ratna Mahamana Pandit Madan Mohan Malviya ji, the founder of Banaras Hindu University, Varanasi. His visionary ideals and lifelong dedication to education and service have created a legacy that endures in this esteemed institution. I am profoundly grateful to my supervisor, **Dr. Om Jee Pandey**, for his invaluable guidance, encouragement, and constructive criticism throughout my Ph.D. journey. His advice and support have been the source of many innovative ideas and the successful completion of this thesis. His confidence in me was a significant source of inspiration, and it has been an honor to work with him over the years. I also extend my deepest appreciation to my research progress evaluation committee members, **Dr. Ajay Pratap** from the Department of Computer Science and Engineering, and **Dr. Priya Ranjan Muduli** from the Department of Electronics Engineering at the Indian Institute of Technology (BHU), Varanasi. Their continuous support, encouragement, and advice have been invaluable. My sincere thanks go to all the professors, office staff, support staff, and Ph.D. research scholars at the Indian Institute of Technology (BHU), Varanasi, India. I also extend my gratitude to my supportive seniors and enthusiastic juniors for their encouragement and support during my Ph.D. work. Finally, I am eternally grateful to my family. And to my husband, **Mr.**

Ankit Pandey, words cannot express the depth of my gratitude. Your patience, unwavering faith in me, and endless encouragement have been my greatest motivation. I am thankful to my parents for their unwavering moral and emotional support throughout this journey.

Date: 21/08/2025

Place: Varanasi


Neha Sharma

List of Figures

1.1	An illustration of IoT ecosystem [1]	2
1.2	Applications of IoT	3
1.3	Illustration of multi-hop data routing in IoT networks with faulty nodes [2]	7
1.4	An IoT network (a) without small-world characteristic (b) with small-world characteristic, demonstrating efficient routing and connectivity with minimal hops	10
2.1	Taxonomy of literature review	21
3.1	An illustration of data routing in multi-hop static IoT networks, with and without node fault prediction	46
3.2	An illustration of normal and outlier data points computed using the LOF framework	50
3.3	Block diagram illustrating the method of energy-efficient and QoS-aware data routing in node fault prediction-based IoT networks	59
3.4	An illustration of node fault prediction analysis in terms of accuracy, precision, and recall values lying between [0, 1]. (a) performance analysis of all the methods over a simulated IoT testbed, and (b) performance analysis of all the methods over a real-world dataset	67
3.5	An illustration of the throughput ratio with varying number of iterations over the network. The throughput ratio is evaluated using the proposed method over (a) a simulated IoT testbed, (b) a real-field dataset and compared with the Q-learning, LEACH, BEEMH, K-means++, NM-LEACH, QL-EEBDG, and direct transmission methods	69

3.6	An illustration of the average data latency (in seconds) with varying number of iterations over the network. The average data latency is evaluated using the proposed method over (a) simulated IoT testbed, (b) real-field dataset, and compared with the Q-learning, LEACH, BEEMH, K-means++, NM-LEACH, QL-EEBDG, and direct transmission methods	70
3.7	An illustration of the network lifetime with varying number of iterations. The total network lifetime is evaluated using the proposed method over (a) a simulated IoT testbed, (b) a real-field dataset and compared with the Q-learning, LEACH, BEEMH, K-means++, NM-LEACH, QL-EEBDG, and direct transmission methods	71
3.8	An illustration of total residual energy of the network with varying number of iterations. The total residual energy of the network evaluated using the proposed method over (a) simulated IoT testbed, (b) real-field dataset and compared with the Q-learning, LEACH, BEEMH, K-means++, NM-LEACH, QL-EEBDG, and direct transmission methods	72
3.9	An illustration of variation of standard deviation (S.D.) of energy consumed over the network with varying number of iterations used for data transmission. The variation of S.D. of the proposed method is evaluated over (a) simulated IoT testbed, (b) real-field dataset, and compared with the Q-learning, LEACH, BEEMH, K-means++, NM-LEACH, QL-EEBDG, and direct transmission methods	73
4.1	An illustration of the time-varying IoT network	79
4.2	An illustration of the (a) variation in the ratio of dead IoDs to total IoDs used for data transmission in the network with each snapshot taken at regular intervals of the mobile network's lifetime and (b) Residual energy with respect to the number of snapshots in a network	96
4.3	An illustration of (a) data throughput and (b) average data latency with respect to the number of snapshots in a network with prevalent data transmission	100
4.4	The analysis of data interference performance in both (a) simulated testbed and (b) real-field IoT testbed	102
5.1	IoT ecosystem: connecting devices for diverse consumer applications	106
5.2	An illustration of data routing in a time-varying IoT network. (a) shows routing without node fault prediction, and (b) demonstrates routing with fault prediction	109

5.3	Method of node fault prediction using autoencoder anomaly detector with fuzzy (ADF) framework	115
5.4	Method of joint node fault prediction and optimal data routing in dynamic IoT networks	125
5.5	Comparative analysis of node fault prediction methods in terms of accuracy, precision, and recall values in the range of [0, 1]. The effectiveness of the suggested approach (ADF) is compared with existing methods, including RF, Fuzzy, K-means, and LOF. Performance analysis of each method across (a) simulated IoT testbed, (b) simulated IoT testbed with changed environment conditions, (c) over real-field dataset, and (d) over real-field dataset with changed environment conditions	131
5.6	A graphic representation of the throughput ratio throughout a range of network iterations. The throughput ratio is evaluated for the proposed method across (a) simulated IoT testbed and (b) real-field dataset, and contrasted against ACR, CRPD, DDR, E-FEERP, and ABR transmission methods	134
5.7	A graphic representation of the average data latency (measured in seconds) as the number of iterations changes across the network. The assessment of average data latency is conducted on proposed approach across both (a) simulated IoT testbed scenarios and (b) real-field datasets. The results are compared with ACR, CRPD, DDR, E-FEERP, ABR transmission methods	135
5.8	A visual representation showcasing the network lifetime across different numbers of iterations. The assessment of the overall network lifetime is conducted through the proposed method across both (a) simulated IoT testbed environments and (b) real-field datasets. The results are compared with the ACR, CRPD, DDR, E-FEERP, ABR transmission methods	136
5.9	A graphic representation of total residual energy throughout a range of network iterations. This evaluation assesses the total residual energy of the network through the proposed method across (a) simulated IoT testbed scenarios and (b) real-field datasets. A comparison is drawn with ACR, CRPD, DDR, E-FEERP, and ABR transmission methods	138
5.10	An illustration depicting the fluctuation in the standard deviation (S.D.) of energy consumption across the network as the number of iterations for data transmission varies. The variation of the S.D. of the proposed method is assessed across (a) simulated IoT testbed and (b) real-field dataset. The results are compared with the ACR, CRPD, DDR, E-FEERP, ABR transmission methods	139

5.11	Convergence curve for auto-encoder model architecture	140
5.12	Confusion matrix for node fault prediction over simulated IoT network . . .	141
5.13	An illustration of training loss of the actor model for 9 possible combinations of learning rates (LRs). The convergence of loss for different combinations is compared to select the best one. Training loss of actor model when (a) actor LR = 0.0001 and critic LR $\in \{0.0001, 0.001, 0.01\}$, (b) actor LR = 0.001 and critic LR $\in \{0.0001, 0.001, 0.01\}$, and (c) actor LR = 0.01 and critic LR $\in \{0.0001, 0.001, 0.01\}$	142
5.14	An illustration of the training loss of the critic model for 9 possible combinations of LR. The convergence of loss for different combinations is compared to select the best one. Training loss of critic model when (a) actor LR = 0.0001 and critic LR $\in \{0.0001, 0.001, 0.01\}$, (b) actor LR = 0.001 and critic LR $\in \{0.0001, 0.001, 0.01\}$, and (c) actor LR = 0.01 and critic LR $\in \{0.0001, 0.001, 0.01\}$	143
6.1	An illustration of joint node fault prediction and data routing over SW-IoT network using ML frameworks	146
6.2	An illustration of (a) conventional IoT network, (b) small-world IoT network after introducing links among the sensor nodes, and (c) small-world IoT network after introducing links between node-gateway pairs	149
6.3	Performance analysis of various algorithms in the presence of fault noise across different metrics. (a) accuracy vs fault noise, (b) precision vs fault noise, (c) recall vs fault noise, and (d) F1-Score vs fault noise, respectively	157
6.4	Performance analysis of various network parameters with varying initial energy of the sensor nodes using different methods of introduction of SWC. Figures (a, b, c) illustrate throughput, latency, and network lifetime variation when long-range links are introduced among the nodes, while Figures (d, e, f) depict the same performance when the long-range links are created between node-gateway pairs	159

List of Tables

2.1	Comparison of Multi-Hop Data Routing Methods in Static IoT Networks	24
2.2	Comparative analysis of ML-based routing protocols in Static IoT networks	26
2.3	Comparative Analysis of Multi-Hop Data Routing Approaches in Time-Varying IoT Networks	29
2.4	Comparative Analysis of Machine Learning-Based IoT Routing Approaches	33
3.1	Terminologies and definitions	45
3.2	Confusion matrix	61
4.1	Terminologies and definitions	80
4.2	Variations in the number of dead IoT devices, alive IoT devices, residual energy, bandwidth utilization, data latency, and data throughput with varying number of iterations used for data transmission over a real field IoT testbed	98
5.1	Terminologies and definitions	110
5.2	Confusion matrix	126
5.3	Sensitivity analysis of ADF Framework across simulated IoT network at different threshold values	139
6.1	Terminologies and definitions	148
6.2	Small-Worldness (SW) Analysis	151
6.3	Performance Comparison of Various RL Algorithms towards Introducing SWC	151
6.4	Performance comparison of the proposed method with various data routing algorithms under similar network conditions	158

Abbreviations

Abbreviation	Description
ABR	Area-Based Routing protocol
ACC	Average Clustering Coefficient
ADF	Auto Encoder Anomaly Detection with Fuzzy Framework
APL	Average Path Length
AR-VR	Augmented and Virtual Reality
BEEMH	Balanced and Energy Efficient Multi-Hop routing
CH	Cluster Head
CIoT	Consumer IoT
CNN	Convolutional Neural Network
CRPD	Clustering Routing Protocol for Dynamic WSNs
DBA	Distributed Bayesian Algorithm
DBSCAN	Density-Based Spatial Clustering
DDR	Dynamic Directional Routing
DDR	Dynamic Directional Routing protocol
DoA	Direction of Arrival
DRL	Deep Reinforcement Learning
E-FEERP	Enhanced Fuzzy Based Energy-Efficient Routing Protocol
EE	Energy-Efficiency
FN	False Negative

Abbreviation	Description
FP	False Positive
HMMs	Hidden Markov Models
IF	Isolation Forest
IoD	IoT Devices
IoT	Internet of Things
LEACH	Low Energy Adaptive Clustering Hierarchy
LMHR	Learning-based Multi-Hop data Routing
LOF	Local Outlier Factor
LPWAN	Low Power Wide Area Network
LSTM	Long Short-Term Memory
ML	Machine Learning
NM-LEACH	Novel Modified Low Energy Adaptive Clustering Hierarchy
PPO	Proximal Policy Optimization
PPP	Poisson Point Process
PSO	Particle Swarm Optimization
RF	Random Forest
RFID	Radio Frequency Identification
RL	Reinforcement Learning
RSSI	Received Signal Strength Indicator
SAC	Soft Actor-Critic
SD	Standard Deviation
SDR	Software-Defined Radio
Sec	Seconds
SEMI-GRU	Semi- Supervised Gated Recurrent Unit
SW-IoT	Small-World IoT
SWC	Small-World Characteristics

Abbreviation	Description
TN	True Negative
TP	True Positive
TS	Transmission Speed
UAVs	Unmanned Aerial Vehicles
V2X	Vehicle-to-Everything
WSN	Wireless Sensor Network

List of Symbols

Symbol	Description
\mathcal{N}, \mathcal{M}	set of N IoDs and set of M gateways, respectively
\mathcal{L}, \mathcal{F}	set of possible links and set of faulty nodes, respectively.
d_{jk}	distance between j th and k th IoDs
d_{max}	threshold distance between j th and k th IoDs
η_{jk}	incidence matrix element corresponding to node- pair j and k
\mathcal{E}, \mathcal{H}	set of residual energies for IoDs and set of a number of hop counts between IoD pairs
$\mathcal{Q}, \mathcal{V},$ and \mathcal{P}	set queue sizes over IoDs, set of transmission power levels from the IoDs, and set of flag bits for the IoDs
$P_k(f)$	flag bit predicting the fault status of k th IoD
L, W	length and width of the network
$D_{jm}^i, E_{jm}^i,$ and T_{jm}^i	transmission delay occurred, data throughput observed, and energy consumed while transferring data from j th IoD to m th gateway at i th iteration of data transmission
p, ℓ	total number of data packets transmitted and length of the data packet

Symbol	Description
$E_{j,(res)}^i$	residual energy of the j th node at i th iteration
\mathcal{I}	interference observed over a node
∂	threshold value of residual energy
$D_{tra.}, D_{pro.}$	transmission and processing delays
$D_{pkt.}, D_{que.}$	packet and queuing delays
$D_{con.}$	delay due to conventional multihop data routing
R_i^m	total data received by m th gateway at i th iteration
R_i^j	total data generated by j th node at i th iteration
β_{jk}^i	data transferred from j th node to k th at i th iteration
S_k^i	state of a sensor node k at i th iteration
D_T, D_R	total data transmitted and total data received
T_D	message hold delay
A_k^i, A_k^z	data point A for k th node at i th and z th iteration
χ	reachability distance
$\Delta(A_k^i, K_k^i)$	distance between data point A and its K th nearest data point
$\psi(A_k^i)$	local reachability density for data point A_k^i
$K_{(A_k^i)}$	K -neighbors of data point A
$\varphi(A_k^i)$	local outlier factor for data point A_k^i
α, γ	learning rate, and discount factor
s, s'	current and next state of the agent
a, \mathcal{A}	action taken to reach the next state, set of actions
$Q(s, a)$	Q-value associated with the action a at state s
ϵ	probability of exploitation
\mathfrak{R}	reward associated with selection of next state
$\mathfrak{R}_E, \mathfrak{R}_T$	reward factors corresponding to residual energy,

Symbol	Description
	data transmission delay
\mathcal{L}_j	set of virtual link for j th node
λ, μ	distribution parameter, mean of Poisson process
$E_{tx}(k, d)$	energy consumed by source IoD to transmit a k -bit data packet to receiver located at distance d
$\varepsilon_e, \varepsilon_{fs},$ and ε_{mp}	energy parameters used to model the energy consumption phenomena during switching on and off the transceiver, data transmission over free space, and multi-path, respectively
η_t^n	sum of normalized energy parameters for IoD n
$\theta, R_{N \times N}, Q_{N \times N}$	data energy, reward matrix, Q-matrix
$Q_{score}, \zeta[]$	accumulated reward over training, IoD array for efficient routing
$\pi(s^n)$	optimal action taken in state s^n
$cs_t^n, pl_t^n, ls_t^n, br_t^n$	channel status, power level, latency, and bandwidth matrices for IoD n
MF_l, MF_m, MF_h	low, medium, and high membership functions
X_k, Y_k	X and Y coordinates of k th sensor node
N_{tr}, y_i	mini-batch size and Q-function target
$\gamma, \mathcal{H}_{target}$	discount factor and target entropy
a'_{i+1}	action sampled from policy at next state
S_{avg}	average size of a data packet