Energy Efficient Intrusion Detection in a heterogeneous environment of Wireless sensor networks

Ayaz Ahmad
Assistant professor, Department of math, National Institute of technology patna, ayaz@nitp.ac.in

Dr Pandarinath Potluri
Professor &principal swarnandhra institute of engineering and technology, sitarampuram, Narsapur , Andhra Pradesh 534280, sriram310@gmail.com

Ajay Reddy Yeruva
Independent Researcher, 1326 Hopyard Road, Apt #62, Pleasanton, CA, USA, 94566, ajayr.yeruva@gmail.com

Potluri Satyasriram
imagineer (data scientist and analyst), Fractal analytics, 4th floor, West Tower Block 2A, Embassy Tech Village, Bengaluru, Karnataka 560103, satyasp.edu2023@gmail.com

Subash Harizan
Department of Computer Science and Engineering, Galgotias University, Greater Noida, Uttar Pradesh, 203201, subashharizan@gmail.com

Rajeev Kumar
Email rajeevsinghs2006@gmail.com, Department of Computer Science and Engineering, Nalanda College of Engineering, Nalanda, Bihar, India - 803108

Deema Mohammed Alsekait
Princess Nourah bint Abdulrahman university, Applied College, Department of Computer Science and Information Technology, Dmalsekait@pnu.edu.sa

Abstract

Few heterogeneous nodes, such as nodes with greater computational capability, can be strategically placed in Wireless Sensor Networks (WSN) to maximize network lifetime availability. Despite the success of many heterogeneous WSN clustering algorithms, finding the ideal network structure remains a difficult task due to the large number of alternative sensor clusters. In this research, we present a method for clustering heterogeneous sensor nodes that uses a Genetic Algorithm to maximize the exhaustion of energy. In the DCHGA, the network's framework is dynamically chosen after each round of message transmission. The average improvement above the 2nd-great performing model (using stable nodes) depending upon the first-node-die and then the last-node-die was 33.9% and 14%,. When compared to state-of-the-art approaches, DCHGA considerably prolonged the life of network. In contrast, the improvement in sensor mobility heterogeneity ranged from 12.7% to 9.9%. The network lifetime was significantly increased by the balanced energy consumption, which also allowed the energy in the sensors to drain gradually. DCHGA's computational efficiency can be compared to that of the competition, and the total average experiment time counted 0.7 seconds having a standard deviation of 0.07 seconds.

Keywords: Dynamic clustering, Energy efficient, Wireless sensor networks, IOT

DOI Number: 10.14704/nq.2022.20.13.NQ88186 Neuro Quantology 2022; 20(13):1493-1503

Overview

In a monitored region, Wireless Sensor Networks (WSNs) are primarily utilized to recognize and process data. A sensor node typically consists of the module of sensors, module of CPU, wireless communication module, & also energy supply

module. The primary purpose of a sensor module is to adapt the information in the immediate environment and process that data. Sensing data is sent and received by the wireless communication module to the base station or other nodes. A battery with a finite amount of energy is used by the energy supply module to provide power to the sensor node. [1]WSNs can be classified as homogeneous or heterogeneous depending on their capabilities for communication, computation, sensing, and initial level power of sensor nodes. Homogeneous WSNs, like bike sharing, are made up of the sensors along with the same processing, sensing, communication, and initial energy capabilities; in contrast, heterogeneous WSNs are made up of sensors with various capabilities. [2]Wireless sensors in the two kinds of WSNs have constrained calculational, energy, and storage resources. By design, sensors are unable to do sophisticated computations or store vast amounts of data, and they are difficult to repair in remote or hazardous locations. The network will halt operating when a node runs out of energy. Energy, as a result, plays a significant role in getting limited lifespan of the WSNs, and a low-energy based clustering strategies shall be used to increase networks longevity.

Clustering leader and the member of nodes make up the clustering structure in WSNs. The data detected by cluster member nodes is gathered and got collected by the head of cluster. Following that, cluster heads are used to send the collected records to the base station. With good scalability, clustering of WSNs could be used in the massive-scale self-maintained networks. A multi-hop technique based on the clustering.[3] The communication cost associated with sensor distribution is a crucial consideration in low-energy network clustering, yet present multi-level clustering algorithms only take the rest energy of the nodes into account when choosing the cluster head.

For WSNs, a variety of clustering strategies are available, including both static and the powerful clustering strategies. Networks built on the static clustering have an unchanging topology once they are constructed. It's possible that certain nodes with less energy left over will be selected as cluster chiefs, which could shorten life. In static clustering networks, the cluster heads experience significant loads and excessive energy consumption. The dynamic clustering technique continuously updates the cluster heads to maintain a balance between their load and consumption when the number of rounds varies.

WSNs' has constrained calculational power, energy, and storage capabilities. Sensors are unable to have sophisticated processing capabilities or a lot of storage. [4]The replacement of sensor nodes with distant and hazardous monitoring locations is inconvenient. Additionally, With the rapid development of the internet of things, WSNs have shown novel qualities in node diversity, complexity, dynamic applicability, and node density. In these new application instances, the networking techniques ought to perform better in terms of QoS and fault tolerance. Dynamic clustering strategies that use less energy and have lower computation costs are therefore needed.

Background of Study

According to [5] the possibility of dispersed spatiotemporal occurrences. This implies that the occurrences can disperse in space like They might move like a tornado or behave like a fire. The writers the utilization of extended linear-chain conditional random fields, which employ a certain set of undirected graphs, a conditional probability distribution's encoding property. Temporal restrictions are added by the authors to a spatial field to identify the network's observations and events' spatiotemporal dependencies. That [6] is a method by which the sensors can identify whether the moment is diffusion or if it's moving or not. The encounter could be settled in our work. or relocating, and we discuss the issue of disclosing the recognition of events for the sink.

Here is an illustration of how to use WSNs for IoT. The tracking of a fire is done using an interior distributed sensor network with a smart processor. If a sensor when the reading surpasses a certain threshold, the sensor node sends the base station's reading and location (or processing unit). A function f is calculated by the base station

Calculate its gradient utilizing the x, y, and z coordinates of the nodes. The outcomes are

displayed as vector plots. [7]The results Greater vectors are found closer to the event's center. A "start sensing process text" is sent by the base station. the 1-hop neighboring of the event nodes' border, must keep monitoring the fire's movement. the origin station is able to determine the event's direction as well utilizing the relatives weighting to the I j, and k in movement elements that make up the gradient. [8]Our work is unique in that several methods. Our capabilities go beyond indoor detection, in our example, the sink and the incidents are both movable, and We make advantage of energy-efficient methods like clustering.

An [9] IoT detection mechanism is presented in the article an artificial neural network to simulate a forest fire a many layer. The back-propagation algorithm for artificial neural networks is used to identify numerous criterion dependent on particular a forest fire's characteristics (such as temperature, radiation, both light). Environmental data gathered by diverse sensors is sent into the neural network. nodes, as well as the appropriate alarm choices. When fresh information is fed into the system, the system can learn from this knowledge and make judgments. In

In [10] this work, we take the stance that the detection is carried out It employed methods that conserve energy in the sensor nodes to lower the WSNs' energy consumption.

The[11] Australian Great Barrier Reef was monitored utilizing an Internet of Things (IoT) application utilizing a hierarchical heterogeneous sensor network and big data analytics. Sensor nodes collect data on the salinity, temperature, and chlorophyll content of the ocean's environment. The sensor nodes collect data, combine it, and send the finished product to a buoy. Poles that the buoys are attached to are in charge of the sending the compiled data towards base station. Using artificial intelligence, the elliptical summaries anomaly detection (ESAD) tool analyses acquired data to find anomalous patterns. The programme determines data inconsistencies, groups related data, and then separates out the anomalous groups.

A sensor that detects an event (also known as a "affected" node") confirms [12]with its neighbor's to see if they also see the event. If every neighbor is impacted, the node declares itself to be non-boundary. Further at least 1 neighbors did not notice the incidence the nodes broadcasts the output of function's. that was calculated depending on the incidence identified and the number of neighbors got impacted. Before continuing, the nodes waited for its neighbors to perform the same function of evaluation. The hubs with the least capability esteem is a limit hub. The information is in this manner shipped off the sink by the limit hub utilizing a multi-jump steering framework. The cycle is rehashed as often as possible to follow changes in the occasion's extent. In our exploration, the calculation ceaselessly tracks the occasion and reports it, notwithstanding any progressions to the occasion's boundaries.

Th[13]e author represents the nodes in a graph, where the edges are fixed and each node is a random variable the likelihood of their interactions. The method contains two stages for detection and reporting. In the initial phase, a model of the events' time dependence is used a first-order Markov chain modelling to complete. in the nodes determine what their perceived values will be in the future. The following phase is the event's spatial dependence model, which fields with Markov entropy. The nodes in this scenario forecast their sensing values utilizing its around neighbors' data. When a node detects an event, it notifies, then they can begin the process of detecting their neighbors the thing.

The [14] paper employs a network made up of a grid of nodes and a Bayesian trust model to follow a diffuse event in the IoT. All nodes have a virtual clustering, with the node acting as the cluster's hub. The neighbours who are within communication range make up its members. The node uses a probability density function to produce a trust index. On the off chance that the trust index esteem is under a predefined edge, the readings from the node don't match at least one of its neighbors' qualities. To change the trust based index, the node utilizes a Bayesian sifting instrument to mix the readings of neighboring nodes with its records. The consequence of this system is either e = 1 or e = 0, where e = 1 indicates that the nodes are recognizing the occasion and e = 0 signifies that it isn't. Each time span T elapses, the node communicates to the sink its Id and the worth of e. The sink reconstructs the network map as well as the course and scale of the event using the

data it has received from the nodes. In our scenario, we suppose that the nodes are not placed in a grid but rather are placed randomly. The nodes that notice the incidence are in charge of reporting it in our event-based clustering.

Model Architecture

An event is what we define as an apparent occurrence of a phenomenon occurring at a particular time and place. A trigger for an atomic incidence is when a one sensor value is greater than a certain limit e (t, s, R), here t denotes time, is the symbol for the thresholds is the place where the incidence takes place when it happens, and R is a logical phrase that specifies the circumstances under which event happens. We employ composite methods to identify complex occurrences. events in which variances in several qualities are found. The following are indicators of a composite event:

$$E\big((e_1 d_1), (e_2 d_2), \ldots., (e_k d_k), C_t, C_s, \delta\big) = (R_1 \wedge R_2 \wedge \ldots. R_k \wedge C_t \wedge C_s \wedge \delta$$

We compare spatial and temporal occurrences. Although our event moves at a given pace and follows a random direction, it keeps its circular shape.

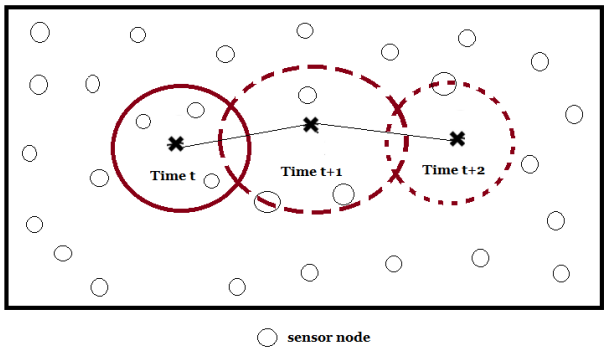


Figure 3: Sensor nodes

Problem Statement

We take into account a heterogeneous WSN with n nodes (N1, N2,..., Nn) and 1 movable sink (S). These nodes are dispersed at the random in region A. A nodes having same beginning energy Einit and communication range Rc. We take into account a portable sink with boundless energy and a Rc communication range. More than one sensing elements from the set "s1, s2,..., sm" are present in each node.

We do not bother with node synchronisation in this work because the nodes have synced clocks. Since the network is heterogeneous, multiple types of sensing devices may be installed on sensor nodes. [15]This happens as a result of nodes having varying sensing capabilities when they are constructed, certain nodes turning off specific sensing components on purpose to conserve energy, and the eventual failure of some sensing components. Events might be stationary or moving. Power, bandwidth, memory, and computation capabilities are all limited on nodes.

Spatio-temporal composite event detection and reporting (STCEDR) in the WSNs

A WSN conveyed in a space A that comprises of n nodes with various detecting parts from the sets s1, s2,..., sm and a portable sink S, as an energy-proficient and disseminated calculation for the recognition and detailing a spatio-fleeting composite occasion E is conceived. The nuclear occasions related with the detecting parts s1, s2,..., sm are utilized to characterize the composite occasion E.

Figure depicts the protocol's essential steps. In Phase 1: Using the sink S's choice of the first anchor A1, a subsequent method. Find Closes tNode is broadcast by S, and After a brief wait, the nodes in the range respond within their ID and remaining energy. The nearest is chosen by the sink depending on strength, of signal and in the event of a tie, node. The smallest ID and rest energy are employed. The Sink S then notifies A1, which is the charge of flooding the composite event E, of the need to monitor the Using Composite Event Request (S, A1, E, δth , hops), E is the composite incidence, and δth is the number of nodes in the network. the composite event's threshold parameter.

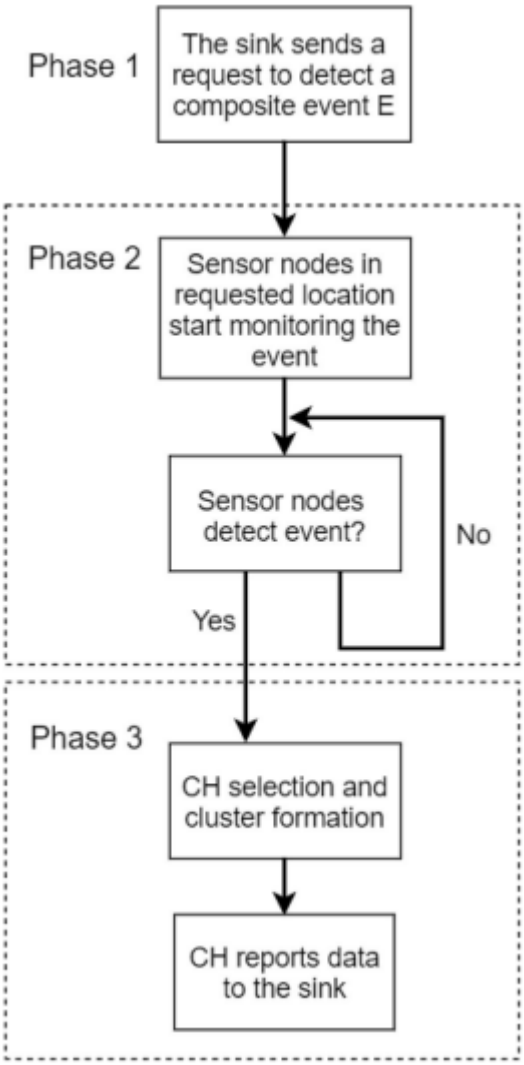


Figure 2: Main phases of ARER

Phase 2: A convergecast tree T with A1 as its root forms as the message deluges the network. Each node Nj will configure its parent Nj after receiving the message. CompositeEventRequest(Nj, E, th, hops) will be sent once more after incrementing the hops field of the message and returning to the sender node. Each node in the convergecast tree T, which is rooted at theA1, has a pointer to its parent at the conclusion of this phase.

Phase 3: The event is first detected by one or more nodes. A cluster is formed by the nodes. Each clustering chooses a clustering head (CH) and starts the incidence reporting process.

Clustering based on events

The only single node that meets the criteria for a CH is one that has detected at least one atomic event and has residual energy over a predetermined level. Based on its remaining energy and ID, a node identifies itself CH and sends a message called New Cluster through cluster hops (which is used to break ties amongst nodes with the same residual energy. The event ID and CH ID are both contained in this message. [16]As long as the number of hops is less than $h_{cluster}$, all nodes within the $h_{cluster}$ hops distances joined the clustering and resent the text. A cluster tree $T_{cluster}$ with the CH as its root is created as the New Cluster message is transmitted. No ack messages will be sent by the nodes to the CH.

Contingent upon the amount of the occasion and quantity of bounces in the New Cluster text, greater than 1 cluster might create. Accumulation happens as text are sent from the cluster individuals to the CH. Nuclear occasions are shipped off the CH by the cluster nodes.

Event coverage

The nodes send the incidence report messages to the CH, along T, to A1, and finally to S. S is movable, therefore A_1 occasionally sends beacons (or the data) to the sink to keep in touch with her. S chooses a new anchor A_2 as follows [17]Where is an input parameter if S doesn't receive a beacon (or data) from the A1 for a while. S broadcasts the message "New Anchor Request" (S, A1). Based on the message's signal strength, node Nj waits a specific amount of time. New Anchor Request before sending a message New Anchor Reply (S, A_1, Nj) to the sink if it receives both S's message and A1's beacons (or data). The node Nj, from where the sink gained the initial answer, serves as the second anchor.

As a result, our data gathering technique is reactive, forming and maintaining its infrastructure only when there are events to record. A CH must identify a route to the sink S if the parent field is no longer valid. Route Request is broadcast by the CH. When S gets the signal, it chooses an anchor A1 utilizing the before mentioned technique. [18]The parameters of the composite event are then broadcast throughout the entire network by A_1 in the form of RouteReply messages. A converge cast tree with A_1 as its root is created as the RouteReply

message is transmitted. Since other clusters frequently develop, A_1 floods the reply message to prevent more Route Request messages from being sent by other CHs.

Be aware that while the tp characteristic may be active on some nodes, it may be obsolete on others. A "constrained flooding" approach, it is essentially an enhanced ring-search mechanism, is developed to reduce energy consumption. [19]The CH transmits the Route Request message to h hops first, sparing the entire network from inundation If the message is received by a node Nj within an active tp attribute, it responds to the CH with a RouteReply message that includes the number of hops to A_1 or, if the shortcut technique was used, the amount of the hops into the last anchor.

Results and discussion

Network's average residual energy for n = 31256 nodes, A.L = 1200 m, medium-sized events, and an average sink speed of 6 m/s is shown in the figure. We change the average event speed to 3 different speeds: 1 m/s, 8 m/s, and 19 m/s. In all of the tests, there is just one ongoing event, which lasts between 30% and 70% of the whole simulation time. For instance, ASC(CF) (30%) indicates that the event lasted 20 minutes, or 30 % of an hour.

ARER(CF&DC) uses less energy than the ASC protocols across all tests. Two types of dynamic clustering (DC) techniques use less energy than ASC (CF).

Average rate of speed m/s	Maximum rate of speed speed m/s
1	4
6	11
12.6	26

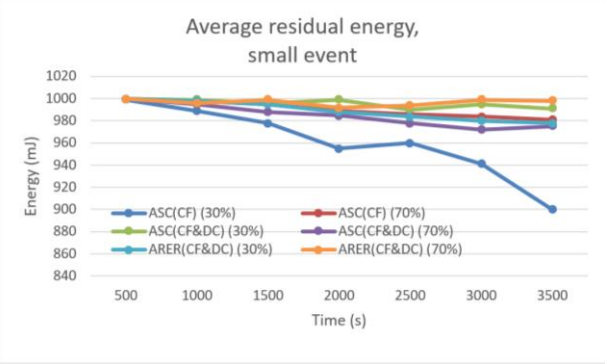
Table 1: Speed of Sink

Average rate of speed speed m/s	Maximum rate of speed speed m/s
1	4
10	14
19	31

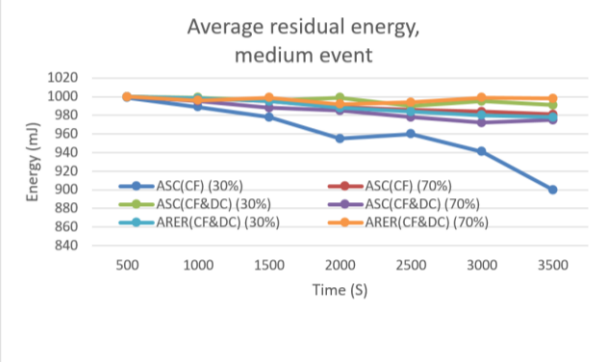
Table 2: Sped of Event

Because nodes joined newly clustering as events develop, few clustering are considered in data reporting.

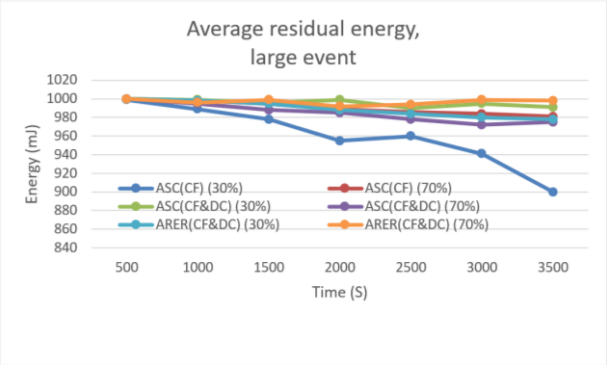
ARER(CF&DC) uses a new clustering technique that does not send acknowledgment messages, making it more energy-efficient than ASC(CF&DC). More clusters are formed as the event moves faster, which lowers the remaining energy. Medium-sized events with an average incidence speed of 10 m/s and A.L = 1200 m. 1 m/s, 6m/s, and 12.6 m/s are the average sink speeds, respectively. It becomes necessary to choose new anchors when the sink is moving more quickly and there are events present in order to keep the clusters and the sink in communication. A new convergecast tree is constructed once the maximum number of anchors has been reached. As a result, this operation requires more energy and is done more frequently.



Graph 1: Average residual energy, small event



Graph 2: Average residual energy, medium event



Graph 3: Average residual energy, large event

Keep 70: 30 ratio in graph

The network has A.L = 1200 m and n = 3126 nodes. The size of the event affects how many clusters there are. More clusters are produced by larger occurrences. More clusters develop as event speeds increase. The number of clusters is influenced by the event's speed since, as was already noted, the event's coverage area fluctuates. Because these numbers are independent, the amount of clusters that form in the network are not impacted by the sink's speed. Due to the dynamic clustering method, ASC(CF&DC) and ARER(CF&DC) contain less clusters than ASC(CF) across all metrics.

In medium incidence with an event pace of 10 m/s, an rate of 36.43% of the nodes joining a clustering had converted clusters at once. A node can switch clusters up to two times, with 1.84 being the average amount of cluster conversion. (For instance, 4 distinct cluster memberships over the course of the experiment as the event changes.)

Both an rise in sink speed and an rise in event speed have a detrimental effect on the % of the composite incidence that the sink correctly processes. [20] A quicker sink speed results in more frequent rebuilds of the convergecast tree, which results in packet losses. Event speed and the frequency of new cluster formation are connected. There is a chance that packets will be lost during cluster formation when entering the cluster and sending acknowledgment messages. When incidence-reporting texts are sent to the sink, there can also be some contention and collisions.

Conclusion

With controlled flooding and dynamic clustering from, the anchor-based routing protocol is enhanced, and this work introduces ARER. We suggest a fresh clustering technique as well as a novel dynamic clustering rule. ARER performs better in terms of the consumption of the energy and accurately detected composite incidence by the sink.

References

1. Kathiroli, P.; Selvadurai, K. Energy efficient cluster head selection using improved Sparrow Search Algorithm in Wireless Sensor Networks. J. King Saud Univ. Inf. Sci. 2021, in press.
2. Nguyen, L.; Nguyen, H.T. Mobility based network lifetime in wireless sensor networks: A review. Comput. Netw. 2020, 174, 107236.
3. Akyildiz, I.F.; Su, W.; Sankarasubramaniam, Y.; Cayirci, E. A survey on sensor networks. IEEE Commun. Mag. 2002, 40, 102–114.
4. Dattatraya, K.N.; Rao, K.R. Hybrid based cluster head selection for maximizing network lifetime and energy efficiency in WSN. J. King Saud Univ.-Comput. Inf. Sci. 2019, 34, 716–726.
5. Nayak, P.; Kavitha, K.; Khan, N. Cluster head selection in wireless sensor network using bio-inspired algorithm. In Proceedings of the TENCON 2019-2019 IEEE Region 10 Conference (TENCON), Kochi, India, 17–20 October 2019; pp. 1690–1696.
6. Kumar, K.; Goswami, M.; Arya, D. Energy-Efficient Clustering of UAVs with Crow Search Interaction. In Proceedings of the 2nd International Conference on Communication & Information Processing (ICCIP), Singapore, 26–29 November 2016.
7. Priyadarshini, R.R.; Sivakumar, N. Cluster head selection based on minimum connected dominating set and bi-partite inspired methodology for energy conservation in WSNs. J. King Saud Univ. Inf. Sci. 2021, 33, 1132–1144.
8. Jain, K.; Kumar, A.; Jha, C.K. Probabilistic-Based Energy-Efficient Single-Hop Clustering Technique for Single-Hop Clustering Technique; Springer: Singapore, 2020; ISBN 9789811533259.

9. Houngbadji, T.; Pierre, S. QoSNET: An integrated QoS network for routing protocols in large scale wireless sensor networks. Comput. Commun. 2010, 33, 1334–1342.
10. Pantazis, N.A.; Nikolidakis, S.A.; Vergados, D.D. Energy-efficient routing protocols in wireless sensor networks: A survey. IEEE Commun. Surv. Tutor. 2012, 15, 551–591.
11. Smys, S. Taxonomy Classification and Comparison of Routing Protocol Based on Energy Efficient Rate. J. ISMAC 2021, 3, 96–110.
12. Djenouri, D.; Zegour, D. Towards Energy Efficient Clustering in Wireless Sensor Networks: A Comprehensive Review. IEEE Access 2021, 9, 92688–92705.
13. Heinzelman, W.R.; Chandrakasan, A.; Balakrishnan, H. Energy-efficient communication protocol for wireless microsensor networks. In Proceedings of the 33rd Annual Hawaii International Conference on System Sciences, Maui, HI, USA, 4–7 January 2000; p. 10.
14. Ma, X.W.; Yu, X. Improvement on LEACH protocol of wireless sensor network. In Applied Mechanics and Materials; Trans Tech Publications, Ltd.: Wollerau, Switzerland, 2013; Volume 347, pp. 1738–1742.
15. Mishra, P.; Kumar, S.; Dangi, P. Design and Comparison of LEACH and Improved Centralized LEACH in Wireless Sensor Network. Int. J. Recent Innov. Comput. Commun. 2021, 9, 34–39. [CrossRef]
16. Al-Zubaidi, A.S.; Mahmmod, B.M.; Abdulhussain, S.H.; Al-Jumaeily, D. Re-evaluation of the stable improved LEACH routing protocol for wireless sensor network. In Proceedings of the International Conference on Information and Communication Technology, Kuala Lumpur, Malaysia, 24–26 July 2019; pp. 96–101.
17. Guhan, T.; Revathy, N.; Anuradha, K.; Sathyabama, B. EEDCHS-PSO: Energy-Efficient Dynamic Cluster Head Selection with Differential Evolution and Particle Swarm Optimization for Wireless Sensor Networks (WSNS). In Evolution in Computational Intelligence; Springer: Berlin/Heidelberg, Germany, 2021; pp. 715–726.
18. Rao, P.C.; Jana, P.K.; Banka, H. A particle swarm optimization based energy efficient cluster head selection algorithm for wireless sensor networks. Wirel. Netw. 2017, 23, 2005–2020. [CrossRef]
19. Jadhav, A.R.; Shankar, T. Whale optimization based energy-efficient cluster head selection algorithm for wireless sensor networks. arXiv 2017, arXiv:1711.09389.
20. Shankar, T.; Shanmugavel, S.; Rajesh, A. Hybrid HSA and PSO algorithm for energy efficient cluster head selection in wireless sensor networks. Swarm Evol. Comput. 2016, 30, 1–10.
21. Rathore, M. S., Poongodi, M., Saurabh, P., Lilhore, U. K., Bourouis, S., Alhakami, W., ... & Hamdi, M. (2022). A novel trust-based security and privacy model for Internet of Vehicles using encryption and steganography. Computers and Electrical Engineering, 102, 108205.
22. Gupta, S., Iyer, S., Agarwal, G., Manoharan, P., Algarni, A. D., Aldehim, G., & Raahemifar, K. (2022). Efficient Prioritization and Processor Selection Schemes for HEFT Algorithm: A Makespan Optimizer for Task Scheduling in Cloud Environment. Electronics, 11(16), 2557.
23. Balyan, A. K., Ahuja, S., Lilhore, U. K., Sharma, S. K., Manoharan, P., Algarni, A. D., ... & Raahemifar, K. (2022). A Hybrid Intrusion Detection Model Using EGA-PSO and Improved Random Forest Method. Sensors, 22(16), 5986.
24. Poongodi, M., Bourouis, S., Ahmed, A. N., Vijayaragavan, M., Venkatesan, K. G. S., Alhakami, W., & Hamdi, M. (2022). A Novel Secured Multi-Access Edge Computing based VANET with Neuro fuzzy systems based Blockchain Framework. Computer Communications.
25. Manoharan, P., Walia, R., Iwendi, C., Ahanger, T. A., Suganthi, S. T., Kamruzzaman, M. M., ... & Hamdi, M. (2022). SVM-based generative adverserial networks for federated learning and edge computing attack model and outpoising. Expert Systems, e13072.
26. Ramesh, T. R., Lilhore, U. K., Poongodi, M., Simaiya, S., Kaur, A., & Hamdi, M. (2022). PREDICTIVE ANALYSIS OF HEART DISEASES WITH MACHINE LEARNING APPROACHES. Malaysian Journal of Computer Science, 132-148.

27. Poongodi, M., Malviya, M., Hamdi, M., Vijayakumar, V., Mohammed, M. A., Rauf, H. T., & Al-Dhlan, K. A. (2022). 5G based Blockchain network for authentic and ethical keyword search engine. IET Commun., 16(5), 442-448.
28. Poongodi, M., Malviya, M., Kumar, C., Hamdi, M., Vijayakumar, V., Nebhen, J., & Alyamani, H. (2022). New York City taxi trip duration prediction using MLP and XGBoost. International Journal of System Assurance Engineering and Management, 13(1), 16-27.
29. Poongodi, M., Hamdi, M., & Wang, H. (2022). Image and audio caps: automated captioning of background sounds and images using deep learning. Multimedia Systems, 1-9.
30. Poongodi, M., Hamdi, M., Gao, J., & Rauf, H. T. (2021, December). A Novel Security Mechanism of 6G for IMD using Authentication and Key Agreement Scheme. In 2021 IEEE Globecom Workshops (GC Wkshps) (pp. 1-6). IEEE.
31. Ramesh, T. R., Vijayaragavan, M., Poongodi, M., Hamdi, M., Wang, H., & Bourouis, S. (2022). Peer-to-peer trust management in intelligent transportation system: An Aumann's agreement theorem based approach. ICT Express.
32. Hamdi, M., Bourouis, S., Rastislav, K., & Mohmed, F. (2022). Evaluation of Neuro Image for the Diagnosis of Alzhimer's Disease Using Deep Learning Neural Network. Frontiers in Public Health, 35.
33. Poongodi, M., Hamdi, M., Malviya, M., Sharma, A., Dhiman, G., & Vimal, S. (2022). Diagnosis and combating COVID-19 using wearable Oura smart ring with deep learning methods. Personal and ubiquitous computing, 26(1), 25-35.
34. Sahoo, S. K., Mudligiriyappa, N., Algethami, A. A., Manoharan, P., Hamdi, M., & Raahemifar, K. (2022). Intelligent Trust-Based Utility and Reusability Model: Enhanced Security Using Unmanned Aerial Vehicles on Sensor Nodes. Applied Sciences, 12(3), 1317.
35. Muniyappan, A., Sundarappan, B., Manoharan, P., Hamdi, M., Raahemifar, K., Bourouis, S., & Varadarajan, V. (2022). Stability and numerical solutions of second wave mathematical modeling on covid-19 and omicron outbreak strategy of pandemic: Analytical and error analysis of approximate series solutions by using hpm. Mathematics, 10(3), 343.
36. Rawal, B. S., Manogaran, G., & Poongodi, M. (2022). Implementing and Leveraging Blockchain Programming.
37. Bourouis, S., Band, S. S., Mosavi, A., Agrawal, S., & Hamdi, M. (2022). Meta-Heuristic Algorithm-Tuned Neural Network for Breast Cancer Diagnosis Using Ultrasound Images. Frontiers in Oncology, 12, 834028.
38. Lilhore, U. K., Poongodi, M., Kaur, A., Simaiya, S., Algarni, A. D., Elmannai, H., ... & Hamdi, M. (2022). Hybrid Model for Detection of Cervical Cancer Using Causal Analysis and Machine Learning Techniques. Computational and Mathematical Methods in Medicine, 2022.
39. Lilhore, U. K., Khalaf, O. I., Simaiya, S., Tavera Romero, C. A., Abdulsahib, G. M., & Kumar, D. (2022). A depth-controlled and energy-efficient routing protocol for underwater wireless sensor networks. International Journal of Distributed Sensor Networks, 18(9), 15501329221117118.
40. Sekar, S., Solayappan, A., Srimathi, J., Raja, S., Durga, S., Manoharan, P., ... & Tunze, G. B. (2022). Autonomous Transaction Model for E-Commerce Management Using Blockchain Technology. International Journal of Information Technology and Web Engineering (IJITWE), 17(1), 1-14.
41. Singh, D. K. S., Nithya, N., Rahunathan, L., Sanghavi, P., Vaghela, R. S., Manoharan, P., ... & Tunze, G. B. (2022). Social Network Analysis for Precise Friend Suggestion for Twitter by Associating Multiple Networks Using ML. International Journal of Information Technology and Web Engineering (IJITWE), 17(1), 1-11.
42. Balasubramaniam, K., Vidhya, S., Jayapandian, N., Ramya, K., Poongodi, M., Hamdi, M., & Tunze, G. B. (2022). Social Network User Profiling With Multilayer Semantic Modeling Using Ego Network. International Journal of Information Technology and Web Engineering (IJITWE), 17(1), 1-14.
43. Dhiman, P., Kukreja, V., Manoharan, P., Kaur, A., Kamruzzaman, M. M., Dhaou, I. B., & Iwendi, C. (2022). A Novel Deep Learning Model for Detection of Severity Level of the Disease in Citrus Fruits. Electronics, 11(3), 495.

44. Dhanaraj, R. K., Ramakrishnan, V., Poongodi, M., Krishnasamy, L., Hamdi, M., Kotecha, K., & Vijayakumar, V. (2021). Random Forest Bagging and X-Means Clustered Antipattern Detection from SQL Query Log for Accessing Secure Mobile Data. Wireless Communications and Mobile Computing, 2021.
45. Maurya, S., Joseph, S., Asokan, A., Algethami, A. A., Hamdi, M., & Rauf, H. T. (2021). Federated transfer learning for authentication and privacy preservation using novel supportive twin delayed DDPG (S-TD3) algorithm for IIoT. Sensors, 21(23), 7793.
46. Poongodi, M., Nguyen, T. N., Hamdi, M., & Cengiz, K. (2021). Global cryptocurrency trend prediction using social media. Information Processing & Management, 58(6), 102708.
47. Poongodi, M., Sharma, A., Hamdi, M., Maode, M., & Chilamkurti, N. (2021). Smart healthcare in smart cities: wireless patient monitoring system using IoT. The Journal of Supercomputing, 77(11), 12230-12255.
48. Rawal, B. S., Manogaran, G., & Hamdi, M. (2021). Multi-Tier Stack of Block Chain with Proxy Re-Encryption Method Scheme on the Internet of Things Platform. ACM Transactions on Internet Technology (TOIT), 22(2), 1-20.
49. Poongodi, M., Nguyen, T. N., Hamdi, M., & Cengiz, K. (2021). A measurement approach using smart-IoT based architecture for detecting the COVID-19. Neural Processing Letters, 1-15.
50. Poongodi, M., Malviya, M., Hamdi, M., Rauf, H. T., Kadry, S., & Thinnukool, O. (2021). The recent technologies to curb the second-wave of COVID-19 pandemic. Ieee Access, 9, 97906-97928.
51. Rawal, B. S., Manogaran, G., Singh, R., Poongodi, M., & Hamdi, M. (2021, June). Network augmentation by dynamically splitting the switching function in SDN. In 2021 IEEE International Conference on Communications Workshops (ICC Workshops) (pp. 1-6). IEEE.
52. Poongodi, M., Hamdi, M., Gao, J., & Rauf, H. T. (2021, December). A Novel Security Mechanism of 6G for IMD using Authentication and Key Agreement Scheme. In 2021 IEEE Globecom Workshops (GC Wkshps) (pp. 1-6). IEEE.
53. Poongodi, M., Hamdi, M., Vijayakumar, V., Rawal, B. S., & Maode, M. (2020, September). An effective electronic waste management solution based on blockchain smart contract in 5G communities. In 2020 IEEE 3rd 5G World Forum (5GWF) (pp. 1-6). IEEE.
54. Poongodi, M., Sharma, A., Vijayakumar, V., Bhardwaj, V., Sharma, A. P., Iqbal, R., & Kumar, R. (2020). Prediction of the price of Ethereum blockchain cryptocurrency in an industrial finance system. Computers & Electrical Engineering, 81, 106527.
55. Poongodi, M., Hamdi, M., Varadarajan, V., Rawal, B. S., & Maode, M. (2020, July). Building an authentic and ethical keyword search by applying decentralised (Blockchain) verification. In IEEE INFOCOM 2020-IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS) (pp. 746-753). IEEE.
56. Poongodi, M., Vijayakumar, V., & Chilamkurti, N. (2020). Bitcoin price prediction using ARIMA model. International Journal of Internet Technology and Secured Transactions, 10(4), 396-406.
57. Poongodi, M., Vijayakumar, V., Al-Turjman, F., Hamdi, M., & Ma, M. (2019). Intrusion prevention system for DDoS attack on VANET with reCAPTCHA controller using information based metrics. IEEE Access, 7, 158481-158491.
58. Poongodi, M., Hamdi, M., Sharma, A., Ma, M., & Singh, P. K. (2019). DDoS detection mechanism using trust-based evaluation system in VANET. IEEE Access, 7, 183532-183544.
59. Poongodi, M., Vijayakumar, V., Ramanathan, L., Gao, X. Z., Bhardwaj, V., & Agarwal, T. (2019). Chat-bot-based natural language interface for blogs and information networks. International Journal of Web Based Communities, 15(2), 178-195.
60. Poongodi, M., Vijayakumar, V., Rawal, B., Bhardwaj, V., Agarwal, T., Jain, A., ... & Sriram, V. P. (2019). Recommendation model based on trust relations & user credibility. Journal of Intelligent & Fuzzy Systems, 36(5), 4057-4064.
61. Jeyachandran, A., & Poongodi, M. (2018). Securing Cloud information with the use of Bastion Algorithm to enhance

Confidentiality and Protection. Int. J. Pure Appl. Math, 118, 223-245.
62. Poongodi, M., Al-Shaikhli, I. F., & Vijayakumar, V. (2017). The probabilistic approach of energy utility and reusability model with enhanced security from the compromised nodes through wireless energy transfer in WSN. Int. J. Pure Appl. Math, 116(22), 233-250.
63. Poongodi, M., & Bose, S. (2015). Stochastic model: reCAPTCHA controller based co-variance matrix analysis on frequency distribution using trust evaluation and re-eval by Aumann agreement theorem against DDoS attack in MANET. Cluster Computing, 18(4), 1549-1559.
64. Poongodi, M., & Bose, S. (2015). A novel intrusion detection system based on trust evaluation to defend against DDoS attack in MANET. Arabian Journal for Science and Engineering, 40(12), 3583-3594.
65. Poongodi, M., & Bose, S. (2015). The COLLID based intrusion detection system for detection against DDOS attacks using trust evaluation. Adv. Nat. Appl. Sci, 9(6), 574-580.
66. Poongodi, M., & Bose, S. (2015). Detection and Prevention system towards the truth of convergence on decision using Aumann agreement theorem. Procedia Computer Science, 50, 244-251.
67. Poongodi, M., Bose, S., & Ganeshkumar, N. (2015). The effective intrusion detection system using optimal feature selection algorithm. International Journal of Enterprise Network Management, 6(4), 263-274.
68. Poongodi, M., & Bose, S. (2014). A firegroup mechanism to provide intrusion detection and prevention system against DDoS attack in collaborative clustered networks. International Journal of Information Security and Privacy (IJISP), 8(2), 1-18.
69. Poongodi, M., & Bose, S. (2013, December). Design of Intrusion Detection and Prevention System (IDPS) using DGSOTFC in collaborative protection networks. In 2013 Fifth International Conference on Advanced Computing (ICoAC) (pp. 172-178). IEEE.
70. Pandithurai, O., Poongodi, M., Kumar, S. P., & Krishnan, C. G. (2011, December). A method to support multi-tenant as a service. In 2011 Third International Conference on Advanced Computing (pp. 157-162). IEEE.