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Survey on Optimization of IoT Routing Based On Machine Learning Techniques

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Abstract: Internet of Things (IoT) is a new paradigm that is supplying enormous offerings for the inventive technology achievements by the researchers. However, there is still a lot of room to deal with various challenges and utilize IoT in different sectors to maximize automation. IoT smart portable devices such as smart phones, home appliances, healthcare gadgets, smart automotive devices, automation industry devices, and so on are linked. Though the use of IoT enabled devices has increased in many fields, the manufacturing sector still faces many connectivity issues due to factors such as device mobility; limited processing power and resource availability, which includes energy, bandwidth constraints, routing cost, and end-to-end delay; communication between nodes via intermediate mobile nodes towards destination may also fail links often, affecting the industry. IoT is rapidly making the world smarter by connecting the physical and digital worlds, and it is anticipated that more than 20 billion devices will be connected by 2024. It gives opportunity, but it also comes a variety of risks. The issue at hand is how to safeguard billions of gadgets, as well as the networks that support they operate. In this paper, we covered numerous IoT-related studies and how routing algorithms are used in methods of machine learning.

Keywords: *Internet of Things, Routing, machine learning, Deep Learning, convolution neural network, support vector machine*

I. INTRODUCTION

IoT is a network of interconnected devices, each with its own unique identification, that automatically gather and exchange data across a network. Connected gadgets collect data and, in some cases, act on it using built-in sensors. The purpose of IoT is to have devices that self-report in real time, increasing efficiency and bringing crucial information to the surface faster. The Internet of Things has the potential to change a wide range of industries. It has a large area that is connected with web-enabled devices and is utilised in a variety of applications ranging from road transportation to intelligent households, health, retail, and supply networks. Kevin Ashton coined the phrase "Internet of Things" in 1999.

The Internet continues to be changing. The internet continues to grow rapidly. Every thing is becoming connected, and each will have its own distinct identity [1]. The current static nature of the internet will be transformed into the extremely dynamic Future Internet, frequently referred to as the Internet of Things. The same way that individuals are linked to the internet, devices are linked to the internet of things. The devices rely on humans to generate all of the information. Humans lack resources such as time, precision, and attention. There is a high demand for machines to behave independently [2,3]. It will significantly reduce waste, costs, and resource loss. The Internet of Things (IoT) has gained prominence in the current context and has as a result. It will significantly reduce waste, costs, and resource loss. The Internet of Things (IoT) has become common in today's environment and has as a massive scientific revolt on workstation in the present digital age that creates an energy to the human life in every field.

Each device in the Internet of Things can be regarded as a route, and a routing algorithm is used when data is shared and transmitted throughout routes. Routing is essential because nodes in an IoT network serve as hosts and routers, supplying data to gateways. Many routing protocols for networks of sensors have been proposed and have been implemented in IoTs. The energy consumption of transmitting nodes is influenced by the routing of data from source to goal. Stochastic methods are a natural way of analysing the energy consumption of each node and the overall network due to the network's random activity.

Furthermore, routing typically incorporates nodes, as evidenced by a significant amount of overhead in the form of beaconing to destinations. During beacons, the source nodes look for flood path/ping-messages from neighbours, that are re-diffused before packets arrive. The destination meets the requirements, and the path is determined. Furthermore, variables such as beacon interval influence the velocity of beacon propagation. The energy and performance effects of routing must also be estimated, as well as the related control and information packet overheads. The Internet of Things is currently seeing an upsurge in threats and security vulnerabilities. Current security approaches could be utilized to counter specific IoT attacks. Traditional tactics, however, may be ineffective in the face of technology improvements, as well as a diversity of assault types and intensity levels. Thus, it is fundamental and critical to connect IoT and Machine Learning (ML) technologies in order to improve their collaboration in a variety of ways.

As a result, enabling ML in IoT for learning and analyzing the behaviors of IoT devices/objects and systems based on prior information and experiences may help the IoT ecosystem to successfully manage the unanticipated deterioration induced by anomalous conditions. As a result, ML approaches have witnessed substantial technological advancement, bringing up a plethora of new research avenues to answer present and future challenges in a variety of fields [4] [5]. IOT exhibit unpredictable dynamics and behaviors, and ML algorithms, in keeping with the nature of IOT, do not require human interaction [6]. However, there are two major difficulties to ML in IOT: node resources and computational restrictions, and the requirement for huge data sets for learning. In terms of IoT network security, one of the most significant issues that ML algorithms confront is the difficulty in applying them to the integrity and confidentiality of security standards. As a result, machine learning algorithms can aid in the enhancement of security in IoT networks. In the next section, we reviewed numerous studies related to machine learning algorithms for routing in IOT.

II.LITERATURE REVIEW

Robert Basomingera et al.,[7] proposed host and cluster-based detection systems that use route caches to detect malicious routes caused by routing misbehavior attacks on control packets. The detection system can be supervised (using labeled data or an exploration network) or unsupervised (using unlabeled data). Although the three techniques perform differently, their use cannot be determined solely by their performance. In contrast, the choice of consumption should be made relatively based on the network's state. If the network's prior state is known, supervised with labeled data can be utilized to generate a training dataset. When the network lasts longer and can be monitored, such a scenario is more possible. When some network details are known or can be anticipated, an exploration network may be employed. Unsupervised is appropriate when the network is completely unpredictable, unmonitored, or short-lived. The proposed methods' complexity is quite low because two of the three recommended ways do not involve training the model on the real test network. Unsupervised learning does not require training, and supervised learning with an exploratory network trains outside of the actual test network. The third method, supervised by labelled data, trains in less than a second, because to the short quantity of the dataset. The simulation uses the DSR reactive routing protocol, but it sheds light on building a more universal technique to adapt to different routing systems. After the cluster head is chosen, the suggested cluster-based detection system is confined to the detection system. The proposed detection methodology is intended to be suitable for any method of selecting a cluster head. However, it is worth mentioning that the cluster head selection procedure causes network issues. The act of picking the cluster head adds overhead to the network (which can be significant if done extensively on a large network). As a result, future expanded study will investigate the impact of cluster head selection overhead on the detection system, as well as quantify the detection scheme's energy and computation resources. An examination of various network variables such as throughput, delays, or latency will allow the systems to be applied to trending ad hoc network applications such as vehicle networks, flying networks, and even IoT-based networks.

Murtadha M et al.,[8] extend method has significantly improved MANET lifetimes compared to existing methods, while maintaining similar packet delivery ratios (PDR) and route generation times. Establishing communications during a disaster or its aftermath is a critical action for conclusion and rescuing survivors. However, during such disasters, the infrastructure required to establish wireless communications, B. Mobile communications affected by the disaster. In this study, a new routing method is proposed to efficiently connect nodes in MANETs to operational BSs to establish communication with survivors during or after a disaster. The proposed method aims to extend the network lifetime by balancing node load and avoiding exhausting nodes with limited remaining power. This goal is achieved using RL. In RL, a neural network predicts routes from nodes to BSs given the network state. Using the proposed method can extend the life of the device, greatly increasing the chances of saving a life. Besides better robustness, the proposed method was able to achieve similar performance in terms of PDR and route discovery time compared to existing routing protocols. Also, since the nodes in wireless networks move at relatively high speeds, the proposed method can provide efficient communication for search and rescue teams during search and recovery of survivors. In future work, the ability to directly generate routes based on MANET input states using generative adversarial networks (GANs) depends on the ability of these neural networks to generate complex multidimensional outputs. The roots used for training the neural network are generated using the method proposed in this work. Therefore, the same route can be generated while significantly reducing the route generation time.

Saeed Kaviani et al.,[9] presents DeepCQ+ routing integrates emerging multi agent deep reinforcement learning (MADRL) techniques into existing Q-learning-based routing protocols and their variants in a novel way, achieving persistently higher performance across a wide range of MANET configurations while training on a limited set of network parameters and conditions. DeepCQ+ routinely outperforms its Q-learning-based competitors in terms of end-to-end throughput and overhead, with an overall improvement in efficiency. In terms of network sizes, mobility circumstances, and traffic dynamics, DeepCQ+ maintains impressively similar performance benefits in numerous cases for which it was not trained. This study presented a successful and practical hybrid approach combining MADRL and CQ+ routing approaches for designing a robust, reliable, efficient, and scalable policy for dynamic wireless communication networks, including numerous instances for which the algorithm was not trained. Our MADRL architecture, in conjunction with the explainable CQ+ structure, is uniquely built for scalability, allowing us to train and test routing policies for varying network sizes, data rates, and mobility dynamics while maintaining consistently excellent performance across scenarios that were not previously trained for. DeepCQ+ routing, a DNN-based resilient routing policy for dynamic networks, is based on CQ-routing but also monitors network statistics to improve broadcast/unicast decisions. DeepCQ+ routing is proved to be far more efficient than typical CQ+ routing systems, with significantly lower normalised overhead (number of transmissions per number of successfully delivered packets). Furthermore, the policy is scalable and employs parameter sharing for all nodes during training, allowing it to reuse the same taught policy in scenarios with varying mobility dynamics, data rates, and network sizes. It should be noted that sharing parameters across all nodes is not required during execution. In the future, we intend to broaden the DeepCQ+ routing action space to include next-hop selection for the unicast mode. Other interesting extensions include extending DeepCQ+ routing to accommodate heterogeneous wireless networks with multiple radio interfaces per node, expanding ACK-based information sharing to include additional context, and accommodating different performance metrics such as end-to-end delay minimization, overhead minimization, and goodput rate maximisation. A further extension of the hybrid DeepCQ+ routing paradigm continues to maintain scalable and robust routing policies, while prioritizing and balancing network metrics to best meet the needs of almost any MANET environment, including heterogeneous MANETs. That's it.

Hossam Farag et al.,[10] proposed method adopts Q-learning at each node to learn the best parent selection policy based on dynamic network conditions. Each node maintains the routing information of neighboring nodes as Q values. It expresses the combined routing cost as a function of congestion level, link quality, and hop distance. The Q value is continuously updated using existing RPL signaling mechanisms. The performance of the proposed approach is evaluated through extensive simulations and compared with existing work to demonstrate its effectiveness. The results show that the proposed method significantly improves network performance in terms of packet delivery and average delay with a small increase in signaling frequency. In this study, an RL-based routing approach was proposed to reduce node congestion and improve routing performance in RPL networks. Each node applies Q-learning to select a preferred parent based on a composite feedback function. The congestion level of each node is incorporated into the RANK metric and distributed using a modified trickle timer strategy. Performance evaluations were conducted to prove the effectiveness of the proposed method to achieve load balancing and improve network performance in terms of packet delivery and average delay.

Pengjun Wang et al.,[11] analyzed to the Deep learning-based routing optimization of a wireless sensor network is described, as is the neural network. This study introduces the subject of route optimization, which is based on wireless sensor network dynamic programming, and then elaborates on its concept and related techniques, as well as develops and analyses the case of wireless sensor network optimization. According to the comparative analysis of the five algorithms in computer simulation, even if the average network delay performance of DPER reached 0.47 s, it could successfully extend the network's life cycle. The DPER method not only increases network life, but it also increases network energy utilization rate, shortens network average path length, and minimizes the standard deviation of the node's remaining energy. Wireless sensor networks installed on site or on each floor of a large building operate in a passive environment for a long time, which limits the time that a wireless sensor network can operate, ie the lifetime of a H. wireless sensor network. Therefore, it is very important to use existing science and technology to extend the lifespan of wireless sensor networks as much as possible so that wireless sensor networks can continue to function without stopping due to power issues. While routing in traditional networks is largely irrelevant to node power sharing, power efficiency of routing algorithms in wireless sensor networks is often more important than finding the shortest path. This study mainly focused on node residual energy and energy uniformity, and proposed an energy routing algorithm for wireless sensor networks based on dynamic programming. In order to extend the life of the network, we use the idea of dynamic programming to generalize the data as much as possible and find efficient ways to ensure the balance of energy consumption of all network nodes. Due to limitations in study time, study conditions, and academic level, this study inevitably has some shortcomings, and further improvements are expected.

Jothikumar et al.,[12] proposed system an Optimal Cluster-Based Routing (Optimal-CBR), Power efficiency and network resilience are improved with a hierarchical routing approach for IoT applications in 5G environments and beyond. The Optimal-CBR protocol uses the k-means algorithm to cluster nodes and a multi-hop approach to chain routing. The clustering phase is called until two-thirds of the nodes are down, after which the consolidation phase is called for the rest of the data transfer. Nodes are clustered using a basic k-means algorithm during the clustering phase, and the highest energy of the node closest to the centroid is chosen as the cluster head (CH). The CH gathers packets from its members and transmits them to the base station (BS). Because two-thirds of the nodes are dead and the leftover energy is insufficient for clustering during the chaining phase, the surviving nodes attempt multihop routing to establish chaining until the data is transferred to the BS. This improves energy efficiency and network lifespan, as demonstrated by theoretical and simulation investigations. The k-means algorithm is used to form clusters in the Optimal Cluster-Based Routing (Optimal-CBR) protocol for organising Internet of Things-based Wireless Sensor Networks. A chaining phase is utilised to establish a routing channel when the residual energy of the CH is less than the threshold energy. The cluster head is chosen based on the Euclidean distance and the residual energy of the node. Because the results of the simulation plots show that Optimal-CBR has a smaller vitality variance within CH and the total remaining entangled vitality is insignificant compared to the k-means, CHIRON, and LEACH-C protocols. , the node will live longer. Expanded. Therefore, current schemes have the potential to evenly distribute power to all network nodes, maximize transmission rounds, and reduce power consumption in 5G setting. Therefore, the proposed system improves the efficiency of sensor nodes by minimizing the power consumption of the nodes and extends the network lifetime. The system does not focus on security aspects when sharing data via a multi-hop routing approach.

Qianao Ding et al.,[13] produced a theoretical hypothetic model formulation of ML as a viable way for constructing a power-efficient green routing model that can overcome the constraints of previous green routing methods. Furthermore, the study presents an overview of previous, current, and future progress in green routing systems in WSNs. This study's findings will be of interest to a wide spectrum of people who are interested in ML-based WSNs. This study expanded on traditional and ML approaches to designing green routing algorithms in WSNs. The study developed a mathematical hypothesis model of an ML-based routing algorithm for increasing the lifetime of WSNs based on comprehensive comparisons and analysis. Furthermore, essential principles and characteristics of various routing algorithms in WSNs are investigated in this study. The research also discusses the advantages and disadvantages of the many strategies that may be utilised to improve the performance of routing algorithms in WSN. Finally, this study discusses the problems of using ML for routing algorithm creation in WSNs, as well as future research objectives that should be addressed and explored with ML. This debate will be of interest to a wide range of people interested in ML and WSNs. Future research work may include the following: Due to the arithmetic bottleneck and energy consumption limitation of WSNs, ML algorithms cannot be deployed at scale in sensors with small computational power and limited energy. However, distributed learning methods require less computational capacity, energy consumption, and smaller memory footprints than centralized learning algorithms (i.e., they do not need to consider the entire network information). Distributed cooperative learning overcomes the arithmetic bottleneck, resulting in ML-based green routing with lower energy usage, which is ideal for WSNs. ML techniques, on the other hand, require a significant amount of computation and energy for effective parameter learning during the training learning phase, making their implementation in WSNs highly difficult. Furthermore, nodes have extremely diverse computational capabilities (for example, the sink has a large computational power, whilst the rest of the nodes are poor), which gives us ideas for how to apply transfer learning in WSNs. Sink nodes can train the model in a distributed manner with other sensor nodes because they have more power and computational capacity. The trained model parameters can then be transmitted to the sensor nodes using sink nodes. After receiving model parameters from various nodes, the sensor nodes multiply these parameters by the corresponding weights and perform a weighted average to obtain their final model parameters, which reduces sensor node training consumption and improves model accuracy in WSNs. Meanwhile, dealing with QoS-aware routing is a difficult task. Satisfying delay restrictions, bandwidth limits, and applying machine learning techniques to design a routing protocol is an intriguing area of research, particularly when applied to WSNs using hybrid ML techniques.

Sapna Chaudhary et al.,[14] established a wireless network algorithm called Optimized Routing in Wireless Networks Using Machine Learning (ORuML). Network type of source and destination nodes. ML models are trained using real-time collected node features such as: B. Battery power usage, available internal storage, node IP addresses and ranges. Intuitively, MLR should outperform ANN and SVM in terms of accuracy and area under the ROC curve (AUC). The proposed algorithm determines whether the source and destination nodes are co-located, and also determines the best neighboring hops for efficient routing. In this research paper, a new His ORuML algorithm for wireless networks is proposed. Machine learning techniques, namely ANN, MLR and SVM, were applied to the NNCF dataset to predict the network type of nodes. Simulations highlight the fact that MLR outperforms KNN and SVM in terms of accuracy and AUC. make a prediction. In addition, the selection of optimal neighbors for efficient routing in MANET or DTN was simulated. As a future extension of current research work, it is proposed that machine learning algorithms such as decision trees and random forests can be applied to specific datasets with network node (NNCF) characteristics. Apart from that, we can apply deep learning to specific datasets and extend the same work to cellular networks. Machine learning can also be used to route messages in opportunistic networks.

Fang Wang et al., [15] Q-Routing is a highly random network environment, and overestimation of values leads to poor performance. To solve this problem, this research proposes an algorithm called Delayed Q-Routing (DQ-Routing). It uses two sets of value functions to perform random delayed updates to reduce value function overestimation and improve the convergence rate. Experiments have shown that the DQ routing algorithm works well for some problems. Traditional routing algorithms cannot dynamically adapt their routing strategies to network fluctuations and are not applicable to increasingly complex network environments. Q-routing algorithms can dynamically adjust their strategy, but overestimation of the value function leads to poor performance in high-random networks. In this study, we proposed a ragged Q-routing algorithm that avoids overestimation of the value function using a ragged estimator. Experiments show that DQ routing not only avoids overestimation of the value function, but also improves the learning rate.

Mahima.v et al.,[16] considerations for Algorithm Development RL-EM outperforms existing algorithms with 40% fewer sleeping nodes and 60% fewer energy overflows using the LEACH protocol. The proposed RL-EM algorithm outperforms LEACH, SEP-M and ACO algorithms in terms of throughput, sleep nodes, power spill and load balancing. Node planning in this research work is done by the RL approach and compared to biologically-inspired algorithms such as ACO and classical probability-based algorithms such as LEACH and SEP-M approaches. The proposed work provides better power management with 40% fewer sleeping nodes and 60% fewer network power overflows compared to the LEACH benchmark protocol. The results of the proposed RL-EM algorithm show even load distribution. The investigative effort also uses maximum resources to achieve the goal of successfully transferring data to the sink. RL-EM avoids energy holes and HOTSPOT problems in networks that other comparison algorithms cannot solve. This algorithm appears to be a new solution to the power management problem in wireless sensor networks.

Maitreyi Ponguwala et al.,[17] MANET-based trust computation techniques were introduced. However, incorrect trust value computation lowers mitigation scheme performance. Thus, the primary goal of this work is to create a novel security method to secure the MANET-IoT from various threats. In this study, a novel group-based routing algorithm with suggestion filtering was suggested, which was backed by security monitors (SMs). The unsupervised machine learning approach is applied for network recommendation filtering. The Secure Certificate-based Group Formation (SCGF) mechanism initially groups the whole network. To compute trust in each group, the Recommendation Filtering by K-means technique (RF-K means) is used. A hybrid optimisation technique that combines the Genetic technique and the Fire Fly Algorithm (GA-FFA) is developed for secure and optimal route selection. Data transmission is protected by a new hashed message authentication code using the High Encryption Standard (HMAC-AES) algorithm, where the hash function is integrated with the encryption function. The MANET-IoT network is secured by a grouping and trust filtering approach. In addition, built-in encryption functions ensure data security and hashing functions ensure data integrity.

Vially Kazadi Mutombo et al.,[18] established EER-RL, an energy-efficient routing protocol based on reinforcement learning. Reinforcement learning (RL) enables devices to adapt to network changes, such as mobility and power levels, to improve routing decisions. The performance of the proposed protocol is compared with other existing low-power routing protocols and the results show that the proposed protocol is superior in terms of power efficiency, network robustness and scalability. In this study, a cluster-based energy-efficient routing protocol for IoT using reinforcement learning called EER-RL was proposed. The aim of this work was to optimize energy consumption and extend network life by finding the best routes for data transmission. Research has produced two versions of the same algorithm. One is cluster-based (EER-RL) and the other is flat-based (FlatEER-RL). More scalable than flat base. However, for small networks it is recommended to use the flat version of the proposed work. EER-RL was designed in three phases, including network construction and CH election. In this study, considering the hop count factor and initial energy, we calculated the initial Q value used for CH selection at this stage. The second step was to form clusters. Each CH sent an invitation to all devices within its coverage area, and each device far from the base station joined the cluster to which the CH was closest. Finally, the data transmission phase, characterized by learning, considered both the device's residual energy and the number of hops to make routing decisions, providing energy-efficient routing. Additionally, an energy threshold for CH substitution was specified. Simulation results showed that EERRL achieved better power consumption and network robustness than his LEACH and PEGASIS. In this study, we used lightweight RL to reduce protocol latency and minimize power consumption. In the future, we would like to explore additional parameters for more optimal routing protocols.

Yuvaraj Natarajan et al.,[19] upgradable cross-layer routing protocol based on CR-IoT was described in order to improve routing efficiency and optimise data transmission in a reconfigurable network. The system is building a distributed controller in this context, which is created with many activities such as load balancing, neighbourhood sensing, and machine-learning path development. On an average of 2 bps/Hz/W, the proposed technique is based on network traffic and load, as well as several other network parameters such as energy efficiency, network capacity, and interference. The testing are carried out using conventional models, demonstrating the reconfigurable CR-IoT's residual energy and resource scalability and robustness. In this study, a machine learning assisted crosslayer routing in a reconfigurable CR IoT application was built.The distributed controller senses the entire environment and generates CR-IoT data to make the best choice for cluster member selection, cluster head selection, and routing path selection. Such ideal selection permits actual data transfer by taking into account the full nature of CR-IoTs, i.e., its properties. The use of three phases with the assistance of ML improves this decision by reconfiguring clusters, thresholds, and CR-IoT based on network requirements. The advantages include making the best use of the CR-IoT network with a controller to enable optimal data transfer with enhanced network level heterogeneity. The cross-layered technique allows for layer cooperation with periodic reconfiguration during the routing process. During the settling phase, the distributed controllers with mutual coordination optimise the processes and therefore the routing paths are deployed. This cross-layer network routing operation strategy improves energy efficiency, network stability, and resource utilisation. The research is also expanded to include the routing operation with channel imperfection effects in heterogeneous cooperative CR-IoTs. Furthermore, the ability to add cloud storage for routing operations would no longer be considered a constraint when changing the routing table.

Mohamed Mira et al.,[20] research focuses on the effectiveness evaluation of the previously indicated selection path mechanisms. In addition, as a considered factor for this evaluation, research will manage two important parameters: power consumption and packet delivery ratio. Different scenarios will be used to simulate what research can find in real-world applications. Finally, research will suggest a strategy based on machine learning contributions to assist us in node deployment according to the specifications of our airport application that research wishes to develop. Several simulations were performed in this study to demonstrate a clear impact on RPL performance by adjusting the transmitting intervals. The machine learning approach used in the previous part validated our findings. However, research should be conducted to develop a prediction model that aids in the deployment of nodes with the best objective function based on input values such as NN, TX, and SI. Furthermore, the predictive model develops an academic technique that can be applied and used in real-world applications, such as our use case of controlling passenger flow at airports. The researchers believe that the ML method established in this study is an excellent starting point for constructing an automated procedure that could be included in any IOT application's data processing section. Future work will focus on how to construct a customer algorithm that collects all of the limitations that can occur in the everyday operation of an IOT application and determines which OF is more suitable.

E. Laxmi Lydia et al.,[21] determined a novel green energy efficient routing approach for IoT applications using DL-based anomaly detection (GEER-DLAD). The provided architecture enables IoT devices to effectively use energy in order to expand network span. To reduce the amount of data transfer across the network, the GEER-DLAD approach employs Error Lossy Compression (ELC). In addition, the moth flame swarm optimisation (MSO) algorithm is used to optimise network path selection. Furthermore, the DLAD method detects anomalies in IoT communication networks using the recurrent neural network-long short term memory (RNN-LSTM) model. A thorough experimental validation procedure is followed, with the findings ensuring that the GEER-DLAD model improves in terms of energy efficiency and detection performance. In This study created an effective GEER-DLAD approach for IoT applications. The provided methodology enables IoT devices to optimally exploit energy in order to increase network span. Initially, IoT devices continuously collect data. They are then compressed using the ELC process. Following that, the IoT devices used the MSO algorithm to execute the routing approach and determine the best path to the destination. The compressed data will be forwarded towards the time after the routes are chosen. The DLAD approach is used during data transmission to detect the appearance of anomalies in IoT communication networks. A thorough experimental validation process is carried out, with the findings ensuring the improvement of the GEER-DLAD model inters of energy efficiency.

Anjaneya Tripathia et al.,[22] using a neural network and real-time measurements, the Optimal Routing with Node Prediction (ORNC) algorithm has been developed to predict the best route for packets. The neural network is trained on node characteristics such as internal storage availability, IP address, battery consumption, and node range. For MANET or DTN network types, an optimal routing algorithm is implemented after categorization. The effectiveness of the approach is compared to that of K-nearest neighbour (KNN), support vector machine (SVM), and multinomial logistic regression (MLR). The ORNC algorithm's major goal is to classify networks as MANET, DTN, or Bluetooth using machine learning techniques as KNN, SVM, MLR, and NN. This classification aids in determining whether or not to use collocation and thus the optimal routing algorithm. The node class type and trust factor are then used to calculate its fitness value, which determines how well it is suited to serve as an intermediate node. The neural network model is determined to be superior among the four ML techniques used in classifying networks as MANET, DTN, or Bluetooth. With this higher accuracy, the optimal hop selection may take place with increased efficacy. These machine learning methods can be utilised to route messages in an opportunistic network as a future expansion of the study work.

Davi Ribeiro Militani et al.,[23] e-RLRP is a research enhanced routing system based on RL that reduces overhead. To compensate for the overhead incurred by the use of RL, a dynamic modification in the Hello message interval is introduced. Various network scenarios with varying numbers of nodes, routes, traffic flows, and degrees of mobility are implemented in order to acquire network characteristics such as packet loss, latency, throughput, and overhead. A Voice-over-IP (VoIP) communication scenario is also implemented, with the E-model method used to forecast connection quality. The OLSR, BATMAN, and RLRP protocols are used to compare performance. Experiment results reveal that e-RLRP minimises network overhead compared to RLRP and, in most circumstances, outperforms all of these protocols when network parameters and VoIP are considered.

The experimental results in this study show that a routing protocol based on RL outperforms existing protocols such as BATMAN and OLSR, notably in Ppl and throughput metrics. These network performance results demonstrate the utility of RL-based routing algorithms for improving computer and ad-hoc networks. The RL approach, on the other hand, adds considerable overhead. As a result, the suggested and developed adjustment method reduced network overhead by reducing the amount of control messages. In terms of throughput and Ppl, the e-RLRP performed better in the majority of the test situations employed in this work, particularly with regard to the Ppl parameter. As a result, it has been proved that the proposed technique minimizes overhead while simultaneously improving network conditions. Reducing network overhead in traditional protocols is an essential strategy since it improves performance. This method is even more essential when novel routing algorithms, such as RL, are utilised to increase network performance while generating more overhead. As a result, an essential contribution of this study is to show how the proposed dynamic modification function can be used to eliminate additional overhead. It is worth noting that several network topologies and settings were used in our experimental tests, including varying numbers of nodes and their drops, as well as different numbers of traffic flows. As a result, it is possible to conclude that RL-based routing algorithms have a considerable favourable impact on the QoE of users in real-time communication services. As a general conclusion, this study emphasises the importance of embedding machine learning algorithms into routing protocols, particularly for ad hoc networks that frequently experience node drops. RL-based routing protocols can help to enhance network conditions, which in turn improves many communication applications. Only the VoIP service is analysed in this study; however, video communication services will be tested in future studies. Furthermore, the established dynamic adjustment method in the sending of Hello messages improved network performance, mostly by lowering overhead, which is an important approach to use in RL-based routing protocols.

Mohammad Shoab et al.,[24] DRL is highly suited to solving optimisation problems in distributed systems in general, and network routing in particular. As a result, a novel query routing strategy termed Deep Reinforcement Learning based Route Selection (DRLRS) based on a Deep Q-Learning algorithm is suggested for unstructured P2P networks. The major goal of this strategy is to improve retrieval efficacy while lowering search costs by reducing the number of connected peers, messages sent, and time spent searching. In this study, a novel strategy to efficiently routing the query to discover the relevant resource was provided. In this context, the query routing problem has been presented as a deep reinforcement learning problem, with a fully distributed method devised to solve it. As a result, the Deep Q-Learning-based query routing algorithm DRLRS is introduced to intelligently select neighbours in order to increase the performance of the P2P network. The results show that the DRLRS learns from past queries and efficiently identifies the best neighbours holding the relevant resource for the current query. The suggested approach consistently improves retrieval efficacy and search cost, outperforming the k-Random Walker and Directed BFS.

Meisam Maleki et al.,[25] presented a bi-objective intelligent routing protocol with the goal of lowering an estimated long-run cost function comprised of end-to-end delay and path energy cost. The routing problem is formulated as a Markov decision process, which captures both the link state dynamics caused by node mobility and the energy state dynamics caused by node rechargeable energy sources. This research proposed adaptive perturbation strategy are a multi-agent reinforcement learning based algorithm to approximate the optimal routing policy in the absence of a priori knowledge of the system statistics. The suggested algorithm is based on model-based RL concepts. More specifically, develop a cost function for each node by deriving an equation for the expected value of end-to-end expenses. The transition probabilities are also calculated live using a tabular maximum likelihood technique. According to simulation results, our model-based approach outperforms its model-free version and behaves similarly to standard value-iteration, which assumes perfect statistics. The bi-objective issue of delay and energy efficient routing in energy collecting MANETs was tackled in this study. Research shows how nodes choose next-hop relays in the presence of link and power dynamics to optimize both end-to-end latency and network lifetime in the long run. To explicitly consider the stochastic dynamics of the network environment, the study modeled the routing problem as a Markov decision process (MDP). In this work, we also proposed an algorithm based on model-based reinforcement learning (RL) to approximate the optimal routing policy of the formulated MDP. Specifically, the researchers modeled the cost function of each node by deriving an expression for the expected end-to-end cost. Also, transition probabilities are estimated online, so a node can perform multiple updates after his single interaction with the system. Moreover, the multi-agent base of the proposed RL method enables global system optimization. As proved by simulations, the proposed scheme converges much faster and converges to better values of the system goal compared to the model-free solution.

Wenjing Guo et al.,[26] proposed the RLLO intelligent routing algorithm. RLLO employs reinforcement learning (RL) to define the reward function while taking into account remaining energy and hop count. It attempts to distribute energy more equally and enhance parcel delivery at no extra expense. This proposed algorithm was evaluated in comparison to Energy Aware Routing (EAR) and Enhanced EAR (I-EAR). The simulation results reveal that RLLO outperforms these two algorithms in terms of network resilience and packet delivery. To extend network lifetime, an intelligent routing algorithm RLLO for WSNs was proposed in this study. Network lifespan is a critical factor for determining the performance of network algorithms in WSN. RLLO takes advantage of the benefits of RL to accomplish global optimisation at no extra expense. To balance energy usage and improve package delivery, define a round reward function. NS2 was used to validate this approach. In terms of the time the first node loses power, the time the network cannot execute packet delivery, and the number of packet deliveries, RLLO outperforms EAR and I-EAR. The inherent advantages of RL algorithms make them suited for dealing with dispersed challenges. A RL-based algorithm was proposed in this work to provide fresh ideas and incentives for solving routing challenges in WSNs. However, there are still concerns that must be addressed. To begin, numerous RL-based WSN routing algorithms have been developed to increase specific performance. The objectives of these RL-based algorithms differ. As a result, it is difficult to compare these methods explicitly. Second, in simulation trials, RLLO has demonstrated to be superior. Future work will be done to evaluate this method in real-world WSN contexts including testbeds and deployments.

Dr. Joy Iong Zong Chen et al.,[27] for enhancing the convergence speed and ant searchability, research has devised termination requirements for the algorithm as well as an adaptive perturbation technique. This permits the discovery of the global best solution. The suggested routing design methodology improves network performance, network life cycle, energy distribution, node equilibrium, network delay, and network energy consumption. The Internet of Things networks, which include wireless sensors and controllers as well as IoT gateways, provide incredibly high functionality. However, little attention is made to optimising the energy consumption of these nodes and enabling lossless networks. With the advancement of artificial intelligence and the popularisation of machine learning, wireless sensor networks and their applications have gradually industrialised and scaled up. Due to the high energy consumption difficulties associated with the routing method, the algorithm protocol achieves the uneven network node energy consumption and local optimum. For providing energy balanced routing at needed locations, the smart ant colony optimisation technique is applied. Based on the smart ant colony optimisation method, a neighbour selection technique is proposed by merging wireless sensor network nodes and energy variables. The development of smart devices and technology has resulted in remarkable growth in the field of IoT. This can be avoided by employing a clever optimisation technique, such as the ACO, and doing dynamic optimisation. The network's energy consumption is optimised, and a global optimal solution is obtained by separating the areas based on delay and energy utilising smart ant colony optimisation and a routing protocol. Machine learning is utilised to investigate energy patterns and reduce energy consumption in these networks. The jump probability is combined based on the node location and the node transmission region, which is divided in order to investigate potential nodes while taking into account the delay and energy of the divided area. The global optimal solution is generated by combining the method's termination criteria, adaptive perturbation technique, neighbour selection strategy, and wireless sensor network with the smart ant colony optimisation algorithm. PSO, ABC, SRT, LRT, and ACO extension algorithms are compared with the ACO for network performance measures and energy delay metric analysis. The efficient implementation of this algorithm results in balanced energy consumption as well as network life cycle extension. The sensor network's delay and energy consumption are taken into account, and the network node's energy consumption is balanced. Even in large size networks, several mobile agents overcome the delay and energy difficulties.

Y. Liu et al.,[28] developed a distributed as well as energy-efficient reinforcement learning (RL) based routing system for the wide area wireless mesh IoT networks. They compare the failure rate, spectrum, and power efficiencies of the proposed algorithm to that of a random routing with loop-detection algorithm and a centralised pre-programmed routing algorithm, which represents the ideal-scenario, using simulations that resemble long-range IoT networks. They also show progressive research to demonstrate how the learning in the algorithm reduces the overall network's power usage. Significant increases in power efficiency, failure rate, and spectrum efficiency have been achieved by utilising RL for routing in IoT/M2M energy sensitive mesh networks. With increasing network scale, the advantage over routing algorithms without learning capability becomes increasingly substantial. Furthermore, the method's significant gain in performance in comparison to the slight addition of complexity clearly illustrates its potential.

III.CONCLUSION

The IoT consists of many different devices that are interconnected and transmit vast amounts of data. The solution starts by collecting data from the nodes and preprocessing it to create a dataset that can be used during the training phase. During the training phase, a decision model is created using machine learning algorithms. This study covers various research papers related to machine learning algorithms for routing in IOT using deep learning algorithms, neural network algorithms, deep learning algorithms, deep reinforcement learning algorithms, convolutional neural networks, and support vector machine algorithms was discussed. In this routing, each node sends its routing decisions to a specific server for all routing operations performed using conventional routing. The data sent includes the decision made and properties such as date and time, source node, destination node, and previous node. Given enough time, the server can use the collected data to build a decision model for each node and make a large number of routing decisions without using traditional routing. We believe such a framework can reduce the resources used for routing and avoid its use entirely.

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