Int. J. Nonlinear Anal. Appl. 13 (2022) 2, 1229–1238
ISSN: 2008-6822 (electronic)
http://dx.doi.org/10.22075/ijnaa.2022.6325

Routing enhancement in wireless sensor networks based on capsule networks: A survey

Hussein Jawad Abdullah*, Mohammed Najm Abdullah

Computer Engineering Department, University of Technology, Iraq

(Communicated by Javad Vahidi)

Abstract

This paper is a survey of an effective routing enhancement for sensor nodes in WSNs. The adoption of WSNs has risen as a result of recent developments in wireless technology (WSNs). Because of its promising properties, such as low cost, low power, simple implementation, and ease of maintenance, a Wireless sensor network has become widely employed for monitoring and controlling applications in our daily lives. In general, scalable and dependable WSN models with shorter latency times, precise data transfer between nodes, low energy consumption, and longer life are required. The performance of a wireless sensor network greatly relies on the routing approach used, so that communications between multiple wireless sensor nodes are managed by routing protocols. To enhance routing in WSNs the following parameters should be considered: Shortest path, energy consumption, network lifetime, mean delay, Mean jitter, Packet delivery ratio, lost packets, throughput and the energy consumption of the entire WSN. The most important constraints of wireless sensor networks are energy consumption and network lifetime. We will use a capsule network to make the enhancement routing in WSNs by enhancing and optimizing routing protocols for WSNs.

Keywords: Capsule Networks, Routing Optimization, Reinforcement Learning
2020 MSC: 90B18

1 Introduction

An unlimited number of small wireless sensor network devices that have the ability to communicate with each other with a limited power. These wireless sensors are used to detect various environmental influences and distributed in real environment to get sensing of different affects. Due to the restricted power of sensor nodes, data acquired from the environment is delivered straight to the BS [11]. A major research topic with the proposed routing algorithms, the routing of energy efficient is still, because the WS has a restricted power supply [35]. Because the applications have a significant impact on the features, which are important in determining which metric(s) to improve, so that routing in wireless sensor networks is a difficult topic. In most circumstances, while determining the appropriate data packet routes, multiple metrics must be considered, like dependability and energy usage, latency and network connectivity, and so on [17]. Wireless sensor nodes are classified as follows according to their functions: nodes that act as sensors and nodes that act as sinks. The environment are sensed by the sensor nodes and it could also convey data to another nodes. The sensor nodes send data to the sink node (BS) which aggregate it. Microsensor, microprocessor, battery,

*Corresponding author
Email addresses: ce.20.11@grad.uotechnology.edu.iq (Hussein Jawad Abdullah), mohammed.n.abdullah@uotechnology.edu.iq (Mohammed Najm Abdullah)

Received: January 2022 *Accepted:* March 2022

transceiver, and memory are the main components of a wireless sensor node [35]. The network life time will be shorten and the rate delay of data transmission will be increased because of Non-linearity is present in the WSN model. To perform accurate data transfer we need to optimize energy of WSN models, so that it is critical to develop approaches for performing that. In order to achieve optimization in energy of the wireless sensor network model, the researchers in this article have designed architectural model of a novel neural network (capsule) [15].

The clustering in wireless sensor networks helps to improve the quality of network by lowering energy usage and increasing data accuracy.

On the basis of network structure, the protocols of routing in WSNs are broadly categorized into 3 primary types: flat-based routing protocols, hierarchical-based routing protocols, and location-based routing protocols are all examples of routing protocols [35].

Enhancing network lifetime in resource-constrained Wireless Sensor Networks (WSNs) has proven to be a major challenge for researchers. Machine learning techniques, specifically reinforcement learning, have been used by researchers to create efficient solutions in the WSN domain [2].

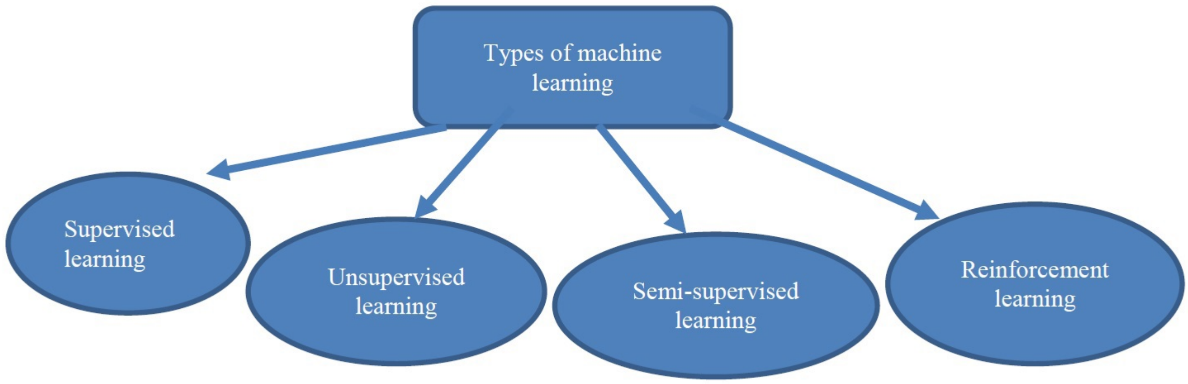

Figure 1: showing the environment ineraction in RL model.

We consider reinforcement learning because it concerns about optimal path. In [21] EAR protocol, which is extension of directed diffusion (DD) applies a set of suboptimal paths, gives more energy and network lifetime than DD.

Reinforcement learning (RL) has been widely utilized in wireless networks to optimize a variety of network parameters, including network lifetime, link quality estimate, energy consumption, and delay. It is the process of learning to map situations to actions in order to maximize numerical rewards associated with those actions. As a result, RL is a computational technique for understanding and automating decision-making and goal-driven learning [2]. Reinforcement learning has shown considerable promise in a variety of difficult activities, such as game play [34]. Searching for neural network architecture [8, 9]. Recommender systems that are iterative [22]. Traditionally, reinforcement learning has been modeled as a Markov decision process (MDP) [39]. To learn a path selection policy, several protocols predominantly use Reinforcement Learning (RL) [48].

Connection stability and shortest path were taken into account as parameters, and the utilization of reinforcement learning was to suggest a strategy for selecting the best neighbor to transmit a packet to the destination at any given time. That is, in respect to the target node, the suggested method used reinforcement learning to anticipate the behavior of the nodes. The suggested method uses a Q-learning algorithm to estimate the value of actions, which has a higher homogeneity [14].

DRL (deep reinforcement learning) has proven to be a successful paradigm, so that it has been used in like radio control, network optimization and resource allocation which are fields of communications concern wirelessly [50].

In [26] to progressively create the topology of a wireless sensor network with the goal of decreasing energy consumption at each sensor, they offered a DRL-TC (deep reinforcement learning-based topology control) algorithm. It has the ability to adapt to environment changes and, to a considerable extent, outperforms other heuristic approaches. In [20] they applied Q-learning and reinforcement learning for enhancing network lifetime and selection optimal routing path through a developed and distributed routing protocols (QLRP and QLTPC). In Q-learning they represented parameters, residual energy and hop length for calculating the Q-value, which used to determine the best next-hop in routing.

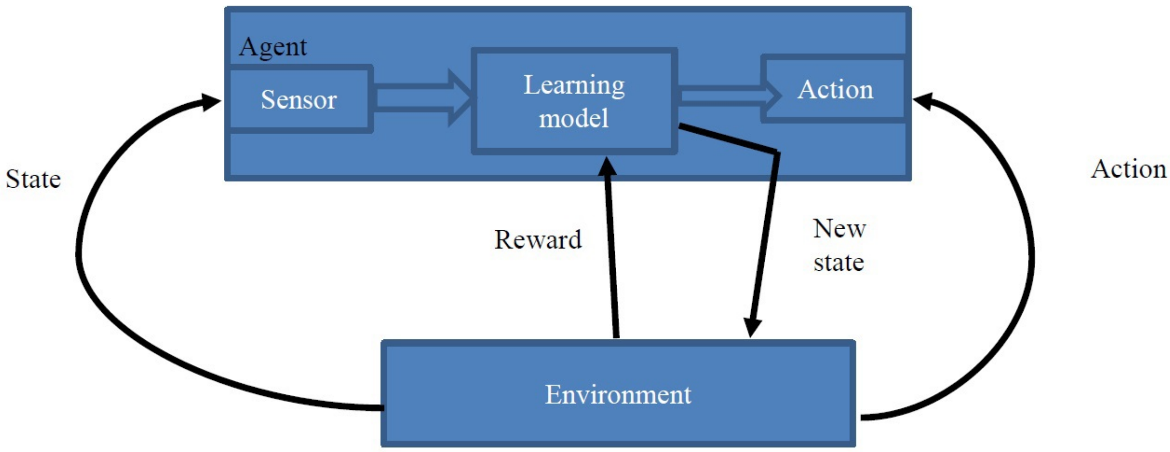

Figure 2: Agent environment interaction in Reinforcement learning model

In this paper [33] to control routing and clustering they presented a new technique of routing. To extend the network's lifespan, they combined gravitational force with fuzzy principles for creating flawless and accurate clusters. A gravitational (routing, clustering) approach developed, to find best solution for routing and clustering. They also employed a fuzzy logic-based deductive inference technique to choose acceptable nodes for cluster head. The method used (EE-MRP), which are based on clustering algorithms, was proposed by the research group in [19]. They divided the network region into phases and evenly distributed cluster heads in it. By the assumption of a threshold in the selection of cluster heads and analysis, the cluster head selection mechanism was improved by avoiding unneeded re-clustering. They incorporated the idea of forwarder node, which has further power and can be altered or recharged, to reduce the distance between cluster heads and base station. All of these techniques increase network throughput while also extending network lifetime.

In [2] using WSNs and fuzzy logic to create a smart irrigation system. In [4] the researchers used techniques of clustering and multiple access to reduce power consumption of wireless sensor networks. In [1] the researchers used WSNs for delivering indoor mail by smart autonomous vehicle. Porposing two routing protocols specifically for flat routing by modifiying ACO algorithm and Naïve Baye's with ranking and using their formulas for choosing candidated neighbors which is the next hop to be less energy consuming [31].

In this paper, we go through related works in section 2 and specifics of routing algorithms for shortest and optimal path in section 3, capsule network in section 4, and conclusion in section 5.

2 Related works

To solve the repeat data transfer, [6] used an intelligent routing technique that used a few well-known optimization algorithms to collect data at each of the cluster heads. The proposed task is carried out using supervised machine learning models. Using fuzzy based approaches, an energy efficient model was designed to deliver a larger bandwidth with minimum energy utilization, directly benefiting the WSN [10]. A unique Neuro-Fuzzy Rule Based Cluster Formation and Routing Protocol has been designed for effective routing in WSNs incorporating IoT [42]. In [36] the researchers applied particle swam optimization which is quantum based algorithm to maximize the average battery capacity for wireless sensor network by selecting optimal cooperative devices of each hop in the routing path.

Sara Sabour et al. [2] they used capsule networks for classifying the MNIST dataset and it well performed compared to convolutional neural network but not as well for CIFAR10, and they maximized network lifetime through efficient dynamic routing between capsules.

In [43] the researcher used a machine learning (capsule networks) with pruning of data technique (removing the least significant capsules) and clustered based routing to solve the limitation of WSN which powered by battery. And they concluded that this proposed method enhanced the metrics of QoS, delay, throughput, energy consumption, packet delivery ratio, and prolonged network life time.

Convolutional neural networks in last years have played a big role in deep learning. And in different domains it proved in tasks of classification to be very successful. Though, the drawbacks of convolutional neural networks in spatiality for objects and the lack in invariance of rotation [2]. To address the lack of spatial orientation in convolutional neural networks the researcher in [2] a novel capsule neural network by using regularization of the reconstruction and dynamic routing, and that capsule neural network going to be invariant of rotation and considering of spatiality. The test errors for MNIST in capsule neural network better than baseline which is 0.25% and 0.39%, respectively.

In [32] Hinton et al. using EM Routing they developed the idea of matrix capsules, for connecting the entity and the position of the viewer they used four by four pose matrix, Which would be modified as well as changes happened in the viewpoints. Adding pose matrix to capsule neural network making it invariant for viewpoint. In [47] including pose matrix for capsules the researcher (in their future work) considered that will make success for the drawback of CapsNets considering complex data. For CIFAR10 they didn't get results.

By classifying the network to three layers (wireless sensor layer, interconnection layer and cloud layer) Govindaraj et al. made optimization for IOTs in WSNs based on capsule network, which performs shortest route selection and CH selection. By learning of capsules for energy to make suitable choice in CH selection. The proposed technique has proven better results in metrics such as increasing the rate of energy efficiency, number of alive nodes, network lifetime and reduction in overhead of the network [17]. In [27] the researchers applied ACO algorithm additional to fuzzy logic to get optimum route in routing model for optimizing the routing in WSNs. Using Firefly and ACO algorithms to make routing in WSNs energy efficient when sending packet from source to sink to get optimal route between them [28], Also the researchers used swarm intelligence (ACO algorithm) to get efficient routing in IOTs [5]. By involving three phases the proposed method applys the routing procedure, which discovers the optimal path in the final phase (route discovery phase) [38].

3 Routing Algorithms

3.1 Shortest Path and Energy Optimization

A lot of research papers included the routing protocols and algorithms for shortest and optimal path selection in wireless sensor network to overcome the challenges and constraints of wireless sensor network like energy consumption and network lifetime which are the most important challenges. In [17] CNN (Capsule neural network) was utilized to create a novel learning model for WSN energy optimization. The model is made up of a layer of wireless sensor with a large number of sensor nodes. Capsule Learning detects acceptable nodes and uses identity records to choose them as CHs within the cluster, as well as shortest path selection for selecting outside the clusters forward nodes, decreasing energy consumption. The network's reliability is improved by choosing the shortest path route using the chosen CH. In [9] to handle the trade-off between the consumption of energy and the optimization of reliability in the routing of wireless sensor networks and to choose the following optimal node of relay the researchers used MOIP (multi objective integer problem). In optimization of multi objective, the idea of Pareto efficient solutions was employed, which gives a sequence of optimal solutions between two objectives. To produce a Pareto set in a short amount of time, by the proposed algorithm NSGA-II which is evolutionary algorithm, by using breadth first search and shortest routes. Employed real case studies by the researchers to demonstrate the outcomes of NSGA-II in large scale and medium scenarios, proving the trade-off between delivery ration and energy efficiency. Moreover, the scalability has no effect on the NSGA-II's performance. The good performance of Non-dominated Sorting Genetic Algorithm II (NSGA-II), which was designed by establishing an initial population biased to the shortest paths, suggests that protocols of routing based on the shortest paths between the sink and sensing SNs could achieve well in cases with topologies identical to the ones evaluated.

In [11] by traveling via each node, the energy-efficient shortest path algorithm discovers the shortest path to all nodes. It is primarily made up of two tables: distance and sequence. The proposed algorithm when compared to other existing routing algorithms, it significantly improves energy savings and network partitioning.

However, the majority of sensor nodes have limited non-rechargeable battery power. As a result, optimizing network energy efficiency by considering heterogeneity among sensor nodes becomes one of the primary challenges in the wireless sensor network routing protocol design with opportunistic routing theory. The network's lifespan will be extended as a result of this. As a result, their goal is to develop an energy-efficient opportunistic routing approach that uses the least amount of power and protects nodes with low residual energy. The outcomes of their research showed that the suggested solution is effective. Shortest path routing protocol that saves energy. By traveling via each node, the energy-efficient shortest path method discovers the shortest path to all nodes. It is mostly made up of two tables. There are two tables: a distance table and a sequence table. ? What is the purpose of a distance table? It is used to determine the shortest distance between any two nodes. The shortest path between any two nodes is found using a sequence table. a table of size N (Number of Nodes) generated by this protocol which updated every O seconds (N3) [11].

In [11] for optimal path choice used location based routing protocols Greedy Perimeter Stateless Routing (GPSR) and Geographic and Energy Aware Routing (GEAR).

In order to identify the optimum path, smart routing protocols have recently begun to use artificial intelligence techniques such as neural network (NN), ant colony optimization (ACO), genetic algorithm (GA), fuzzy logic (FL), and others. These algorithms improve network performance by adapting to changes in the wireless sensor network topology, the energy problem, and the complexity of the environment, and altering through intelligent behavior [16].

The main goal of the contribution in this research is to produce the best network node selection possible. In the environment of WS, to maximize the utilization of network energy by selecting the most suitable nodes. Perform effective route selection to detect the nodes [17].

Because the sensor node's energy is mostly used for data receiving and transmitting [49], the typical routing protocol focuses on finding the shortest way to send data as soon as possible from the source node to the destination.

In [40] based on DS (Dempster–Shafer) evidence theory, the researchers proposed a reliable routing algorithm and an efficient energy relied on DS evidence theory (DS-EERA) and to determine the next hop, to fuse the basic probability assignment (BPA) function of each index value the DS evidence theory fusion rule is used. It can help to extend the network's lifespan. In the meantime, it can improve data transmission reliability and achieve a lower packet loss rate.

In [17] the developed model, by selection of the best nodes in a WS environment, wants to enhance the energy efficiency of the network. Using ACO for finding optimal routing in WSNs using the shortest path and the residual energy of the whole network, As a result they get the lifetime of the network to be prolonged [12].

The researchers used A star algorithm to find the optimal path through energy parameter getting the routing to be efficient [13]. The proposed algorithm used the neighbouring and clustering technique to deliver data to the base station (optimal path) [3]. The researchers used the second type of fuzzy neural to optimize the energy for IOTs in WSNs [30].

4 Capsule Network

A capsule is a collection of neurons whose outputs represent several aspects of the same entity. A capsule network has multiple layers, each of which contains many capsules [15].

Hinton and his assistant proposed the capsule network in October 2017, to describe the probability of the feature's existence, by using the length of the capsule's activation vector, and to represent the parameters of the corresponding instance by using the direction of the capsule's activation vector [32].

[17] In optimization and routing tasks, to be efficient, a feasible neural model which is the architecture of CNN (capsule neural network) has been shown. For the WSN, the architecture of the model is developed to obtain improved performance by decreasing the overhead of network energy. The primary contribution of this research is the development of a novel neural network architecture for increasing the performance of sensor network and network overhead optimization. These neural models of machine learning for IoTs in WSN were developed in this paper due to their dynamic behavior, robustness, ability to be used to a variety of applications. The main goal of the machine learning model in this research, the capsule neural model, in order to arrive at the best selection of network node, by investigating the previous historical behavior of the SNs. The fundamental work contribution of this paper is the modeling and development of a novel CNN architecture model for optimizing the performance of sensor network and network overhead optimization. The proposed modelled capsule neural network architecture is feasible and has been shown to be useful for routing and optimization activities.

CNNs, based on hierarchical links, it builds structures and mimics the neural system. Unlike convolutional neural network, which loses a lot of information on the object's spatial location, which is important for segmentation and detection. Geoffrey Hinton introduced the capsule neural network which considered the rescue to the convolutional neural network's deficiencies. The input, hidden, and output layers are the three basic components of the CNN architecture. The hidden layer additionally has three additional layers: the convolutional layer, primary capsules and lower and high layer also known as digi-caps [45].

As a comparison to the convolution neural network, the CapsNet significantly improves the performance of identifying overlapped images and sound [44].

Because of incapability of realizing object rotations of convolutional neural networks and the presence of scaling inside objects, CNNs outperform convolutional neural networks in the detection and quantification of structural defects [7]. In capturing the required information, the capsule in the current CNN resembles the human brain [37], With better learning and better resolution than convolutional neural network by dividing the images into subparts and hierarchically connecting the parts [41], The Convolutional neural network's pooling layer ignores feature location relationships, resulting in performance deterioration; whereas, the capsule exhibits good feature extraction, improving classification accuracy [46]. The researchers used capsule network to optimize the performance in text classification and to recognize handwritten indic character [23, 24]. Using capsule network to predict and classify the morphology of galaxy [18]. To efficiently route a little number of capsules among layers, the researchers suggested a non-repetitive routing algorithm which exploits a self-attention technique [25].

In contrast to previous neural networks that were composed of neurons, CNNs consist of a large number of capsules, each having its own meaning and direction. Neuronal activity within the capsule is activated to represent different characteristics of a given feature within the image. Many different sorts of instantiation characteristics can be included in these attributes, including posture (position, size, and direction), deformation, reflectivity, velocity, texture, and tone. The CNN has a lot of layers at the network level. There are lowest and higher levels of capsules the first called vector capsules and the other called routing capsules for the lowest, as input, use just a tiny part of the image which called the perceptual domain and in this level tried to discover whether a specific pattern exist and how it is posed. While in the higher used to discover objects which are more complex and larger. The possibility of the presence of an object is represented by the length of output vector of the capsule, and the parameters for object attitude are recorded by its direction. If slightly changed the position of the pattern, same length will output of the vector of the capsule rather than there will be a small change in its direction. As a result, the capsules have an isotropic effect. If a capsule which is eight dimensional output of the CNN, for example, the possibility of the object's presence represented by its vector length, and the object's different parameters represented by the direction of the vector in the space of its eight dimensional, such as how much of rotation angles or its accurate position. The capsule network's activation vectors are interpretable, and it exceeds the convolutional neural network in classification accuracy using the MNIST dataset. Despite the study's benefits, it was also shown that capsules are incompatible with large datasets and complicated problems. Literature also revealed that the capsule's and convolutional neural network classification's power requirements are considerable [32]. Figure 3 showing the capsule.

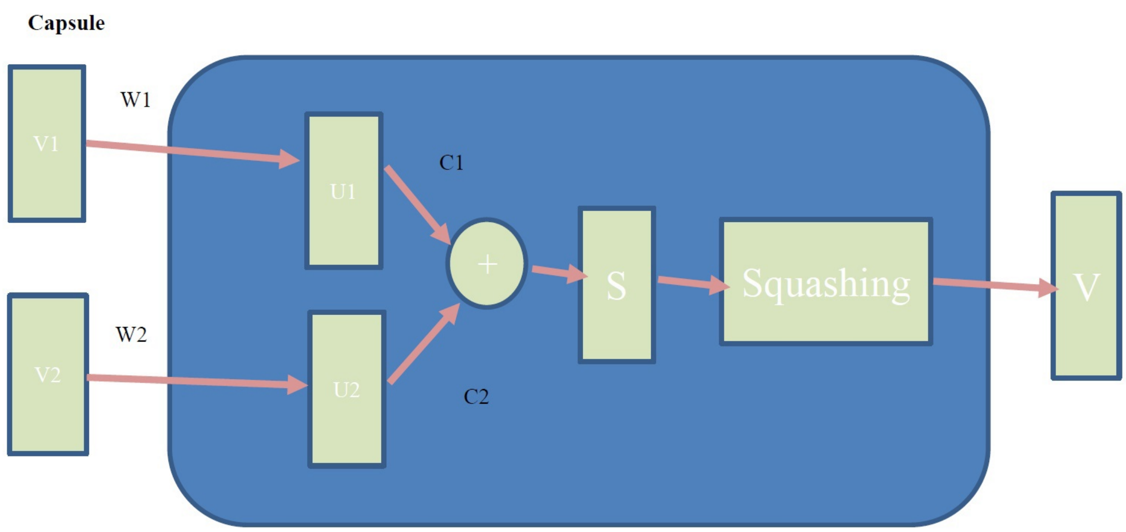

Figure 3: Capsule

4.1 Calculation of capsule

$$u1 = w1v1$$

$$u2 = w2v2$$

$$s = c1u1 + c2u2$$

$$v = Squash(s)$$

$$v = \frac{\|S\|^2}{1+\|S\|^2}\frac{S}{\|S\|}... \tag{4.1}$$

4.2 Dynamic Routing Between Capsules

In [2] the architecture of capsule network is composed of two layers which are convolutional and one layer which are fully connected. The first one (ReLU Conv1) with 256 channels and 9×9 filter and the second layer (primaryCaps) with 32 channels and eight dimensions for each. The last layer (DigitCaps) with 10 capsules where each length of it represent the probability object existence. Wherein the CapsNets showed in tests best accuracy (less error) for MNIST dataset than others (like convolutional neural network). Also the capsule networks better than convolutional neural network in discovering two overlapping digits (MultiMNIST dataset). While in another datasets (CIFAR10) the capsule networks don't perform as well there. The researchers make advantage of an iterative mechanism called routing by agreement where a lower level capsule prefers to deliver its output to higher level capsules with large scalar products for their activity vectors and the prediction from the lower-level capsule, the goal of this study is to demonstrate that one simple solution works well and that dynamic routing is beneficial.

Agreement between two capsules (capsule a, capsule b) is executed to get a single primary prediction of one capsule to the class of the other one. If the level of agreement is high, the two capsules are related. As a result, the coupling coefficient will be raised, whereas it would normally be reduced [29].

Table 1: Summary for optimal (shortest) path and energy efficiency routing protocols

authors	algorithm	Routing protocol	objective	classification
Singh, Harmeet [35]		Greedy Perimeter Stateless Routing (GPSR)	best path choice	based on location_best path
Singh, Harmeet [35]		Geographic and Energy Aware Routing (GEAR)	Optimal path choice	Based on location_optimal path
Marlon Jeske, et al. [17]	NSGA-II BFS	Collection Tree Protocol (CTP)	energy efficiency, reliability	Hierarchical protocol
M. Selvi, et al. [33]	Gravitational Clustering	Gravitational Routing	energy efficiency, network lifetime, delay	Hierarchical Protocol
P.S. Lingam, et al. [21]	The proposed algorithm	Energy efficient protocol	shortest path to all nodes	hybrid
P.S. Lingam, et al. [21]		OLSR ROUTING PROTOCOL	By using MPR (multipoint relays): reduces the control traffic overhead, shortest path to a destination	proactive
A. Kundaliya, D.K. Lobiyal [20]	Reinforcement learning	Q-Routing	Optimal path, Enhance lifetime of network	Reactive
M. Elshrkawey, et al. [11]	Schedules of TDMA	MOD-LEACH	Network lifetime and energy efficiency	Hierarchical Protocol
M.K. Khan, et al. [19]		EE-MRP	network lifetime, throughput, and energy efficiency	Hierarchical Protocol
P.S. Lingam, et al. [21]		EAR	Prolong network lifetime, for communication it makes a group of suboptimal paths	Data centric protocol
Liangrui Tang, et al. [28]	DS and BPA	DS-EERA	Prolong network lifetime, data transmission reliability is enhanced, a loss rate of a packet is lowered, and Shortest path	hybrid

5 Conclusion

In this paper, we make a survey about wireless sensor network optimizing by enhancing routing in WSN considering the most constrained challenges of WSN, which are the energy efficiency and network lifetime with routing algorithms and reinforcement machine learning for selecting the optimal path. And going through the capsule network's architecture, routing and calculation, which is our objective to enhance the wireless sensor network routing.

References

[1] M.N. Abdullah and M.J. Ahmed, *Intelligent autonomous vehicle for indoor mail delivery using wireless sensor network*, Iraqi J. Comput. Commun. Control Syst. Eng. **19** (2019), no. 4, 12—19.

[2] M.N. Abdullah, M.S. Croock and A.K. Mousa, *Automation of smart irrigation system based on wireless sensor network*, Sens. Lett. **13** (2015), no. 1, 92-–97.

[3] A.A. Alkadhmawee, M.A.H. Hasab and E.W. Abood, *Clustering and neighbouring technique based energy-efficient routing for WSNs*, Karbala Int. J. Mod. Sci. **7** (2021), no. 2, 151—159.

[4] O.N. Al-Khayat, S.Y. Ameen and M.N. Abdallah, *WSNs power consumption reduction using clustering and multiple access techniques*, Int. J. Comput. Appl. **87** (2014), no. 9, 33-–39.

[5] D. Arulanantham, C. Palanisamy, G. Pradeepkumar and S. Kavitha, *An energy efficient path selection using swarm intelligence in IoT SN*, J. Phys.: Conf. Ser. **1916** (2021), no. 1.

[6] G.R. Asha and A. Gowrishankar, *Energy efficient clustering and routing in a wireless sensor networks*, Procedia Comput. Sci. **134** (2018), 178—185.

[7] J.E. Barraza, *A capsule neural network based model for structural damage localization and quantification using transmissibility data*, MSc Thesis, Mechanical Engineering Department, Faculty of Physical Sciences and Mathematics, University of Chile, 2019.

[8] H. Cai, T. Chen, W. Zhang, Y. Yu and J. Wang, *Efficient architecture search by network transformation*, 32nd AAAI Conf. Artif. Intell. **AAAI** (2018), 2787—2794.

[9] H. Cai, J. Yang, W. Zhang, S. Han and Y. Yu, *Path-level network transformation for efficient architecture search*, 35th Int. Conf. Mach. Learn. ICML **2018** (2018), no. 2, 1069—1080.

[10] M. Collotta, G. Pau and D.G. Costa, *A fuzzy-based approach for energy-efficient Wi-Fi communications in dense wireless multimedia sensor networks*, Comput. Networks **134** (2018), 127-–139.

[11] M. Elshrkawey, S.M. Elsherif and M.E. Wahed, *An enhancement approach for reducing the energy consumption in wireless sensor networks*, J. King Saud Univ. - Comput. Inf. Sci. **30** (2018), no. 2, 259—267.

[12] Z. Enxing and L. Ranran, *Routing technology in wireless sensor network based on ant colony optimization algorithm*, Wirel. Pers. Commun. **95** (2017), no. 3, 1911-–1925.

[13] A. Ghaffari, *An energy efficient routing protocol for wireless sensor networks using a-star algorithm*, J. Appl. Res. Technol. **12** (2014), no. 4, 815-–822.

[14] A. Ghaffari, *Real-time routing algorithm for mobile ad hoc networks using reinforcement learning and heuristic algorithms*, Wirel. Networks, 23 (2017), no. 3, 703-–714.

[15] S. Govindaraj and S.N. Deepa, *Network energy optimization of IOTs in wireless sensor networks using capsule neural network learning model*, Wirel. Pers. Commun. **115** (2020), no. 3, 2415—2436.

[16] W. Guo and W. Zhang, *A survey on intelligent routing protocols in wireless sensor networks*, J. Netw. Comput. Appl. **38** (2014), no. 1, 185-–201.

[17] M. Jeske, V. Rosset and M. C.V. Nascimento, *Determining the trade-offs between data delivery and energy consumption in large-scale WSNs by multi-objective evolutionary optimization*, Comput. Networks **179** (2020), 107347.

[18] R. Katebi, Y. Zhou, R. Chornock and R. Bunescu, *Galaxy morphology prediction using capsule networks*, Mon. Not. R. Astron. Soc. **486** (2019), no. 2, 1539-–1547.

[19] M.K. Khan, M. Shiraz, K.Z. Ghafoor, S. Khan, A.S. Sadiq and G. Ahmed, *EE-MRP: energy-efficient multistage routing protocol for wireless sensor networks*, Wirel. Commun. Mob. Comput. **2018** (2018).

[20] A. Kundaliya and D.K. Lobiyal, *Q-Learning based routing protocol to enhance network lifetime in WSNs*, Int. J. Comput. Networks Commun. **13** (2021), no. 2, 57—80.

[21] P.S. Lingam, S. Parthasarathi and K. Hariharan, *Energy efficient shortest path routing*, Int. J. Innov. Res. Adv. Eng. **4** (2017), no. 6, 72-–79.

[22] F. Liu, R. Tang, X. Li, W. Zhang, Y. Ye, H. Chen and Y. Zhang, *Deep reinforcement learning based recommendation with explicit user-item interactions modeling*, arXiv:1810.12027v3, (2018).

[23] B. Mandal, S. Dubey, S. Ghosh, R. Sarkhel and N. Das, *Handwritten indic character recognition using capsule networks*, IEEE Appl. Signal Process. Conf. ASPCON, 2018, p. 304-–308.

[24] J.S. Manoharan, *Capsule network algorithm for performance optimization of text classification*, J. Soft Comput. Paradig. **3** (2021), no. 1, 1-–9.

[25] V. Mazzia, F. Salvetti, M. Chiaberge, *Efficient-CapsNet: capsule network with self-attention routing*, Sci. Rep. **11** (2021), no. 1, 1-–13.

[26] X. Meng, H. Inaltekin and B. Krongold, *Deep reinforcement learning-based topology optimization for self-organized wireless sensor networks*, IEEE Global Commun. Conf. (GLOBECOM), 2019, p. 1–6.

[27] V.M. Mualuko, P.K. Kihato and V. Oduol, *Routing optimization for wireless sensor networks using fuzzy ant colony*, Int. J. Appl. Eng. Res. **12** (2017), no. 21, 11606—11613.

[28] M. Okwori, M.E. Bima, O.C. Inalegwu, M. Saidu, W.M. Audu and U. Abdullahi, *Energy efficient routing in wireless sensor network using ant colony optimization and firefly algorithm*, CEUR Workshop Proc. **1830** (2016), 236—242.

[29] M.K. Patrick, A.F. Adekoya, A.A. Mighty and B.Y. Edward, *Capsule networks: A survey*, J. King Saud Univ. Comput. Inf. Sci. **34** (2022), no. 1, 1295–1310.

[30] D. Rasi and S.N. Deepa, *Energy optimization of internet of things in wireless sensor network models using type-2 fuzzy neural systems*, Int. J. Commun. Syst. **34** (2021), no. 17, 4967.

[31] Y.S. Razooqi and M. Al-Asfoor, *Enhanced ant colony optimization for routing in WSNs an energy aware approach*, Int. J. Intell. Eng. Syst. **14** (2021), no. 6, 442-–452.

[32] S. Sabour, N. Frosst and G.E. Hinton, *Dynamic routing between capsules*, Adv. Neural Info. Process. Syst. **30** (2017), 3857-–3867.

[33] M. Selvi, S.V.N. Santhosh Kumar, S. Ganapathy, A. Ayyanar, H. Khanna Nehemiah and A. Kannan, *An energy efficient clustered gravitational and fuzzy based routing algorithm in WSNs*, Wirel. Pers. Commun. **116** (2021), no. 1, 61-–90.

[34] D. Silver, J. Schrittwieser, K. Simonyan, I. Antonoglou, A. Huang, A. Guez and D. Hassabis, *Mastering the game of go without human knowledge*, Nature **550** (2017), no. 7676, 354-–359.

[35] H. Singh, M. Bala and S.S. Bamber, *Taxonomy of routing protocols in wireless sensor networks: A survey*, Int. J. Emerg. Technol. **11** (2020), no. 1, 43-–53.

[36] L. Song, K.K. Chai, Y. Chen, J. Loo, S. Jimaa and Y. Iraqi, *Energy efficient cooperative coalition selection in cluster-based capillary networks for CMIMO IoT systems*, Comput. Networks **153** (2019), 92-–102.

[37] K. Sreelakshmi, S. Akarsh, R. Vinayakumar and K.P. Soman, *Capsule neural networks and visualization for segregation of plastic and non-plastic wastes*, 5th Int. Conf. Adv. Comput. Commun. Syst. ICACCS, 2019, p. 631-–636.

[38] K. SureshKumar and P. Vimala, *Energy efficient routing protocol using exponentially-ant lion whale optimization algorithm in wireless sensor networks*, Comput. Networks **197** (2021), 108250.

[39] R.S. Sutton and A.G. Barto, *Reinforcement learning: An introduction*, MIT Press, 1998.

[40] L. Tang, Z. Lu and B. Fan, *Energy efficient and reliable routing algorithm for wireless sensors networks*, Appl.

Sci. **10** (2020), no. 5.

[41] J.K. Teto and Y. Xie, *Automatically identifying of animals in the wilderness: Comparative studies between CNN and C-capsule network*, 3rd Int. Conf. Comput. Data Anal., 2019, p. 128—133.

[42] K. Thangaramya, K. Kulothungan, R. Logambigai, M. Selvi, S. Ganapathy and A. Kannan, *Energy aware cluster and neuro-fuzzy based routing algorithm for wireless sensor networks in IoT*, Comput. Networks **151** (2019), 211—223.

[43] S. Umamaheswari, *Capsule network-based data pruning in wireless sensor networks*, Int. J. Commun. Syst. **33** (2020), no. 5.

[44] F. Vesperini, L. Gabrielli, E. Principi and S. Squartini, *Polyphonic sound event detection by using capsule neural networks*, IEEE J. Sel. Top. Signal Process. **13** (2019), no. 2, 310-–322.

[45] T, Vijayakumar, *Comparative study of capsule neural network in various applications*, J. Artif. Intell. Capsul. Networks, **1** (2019), no. 1, 19-–27.

[46] Z. Wang, L. Zheng, W. Du, W. Cai, J. Zhou, J. Wang and G. He, *A novel method for intelligent fault diagnosis of bearing based on capsule neural network*, Complexity **2019** (2019), Article ID 6943234.

[47] E. Xi, S. Bing and Y. Jin, *Capsule network performance on complex data*, arXiv preprint arXiv:1712.03480, 10707 (2017), 1-–7.

[48] W. Xia, C. Di, H. Guo and S. Li, *Reinforcement learning based stochastic shortest path finding in wireless sensor networks*, IEEE Access **7** (2019), 157807-–157817.

[49] J. Yan, M. Zhou and Z. Ding, *Recent advances in energy-efficient routing protocols for wireless sensor networks: A review*, IEEE Access **4** (2016), 5673—5686.

[50] C. Zhang, P. Patras and H. Haddadi, *Deep learning in mobile and wireless networking: A survey*, IEEE Commun. Surv. Tutor. **21** (2019), no. 3, 2224—2287.