Reinforcement Learning-Based Efficient Data Collection in Sink Wireless Sensor Network

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ABSTRACT

The Wireless Sensor Networks (WSNs) is a kind of ad-hoc network of interconnected sensors to observe surrounding environment and record real-time values as the environment changes from time to time. The main source of the power supply for sensors in WSNs is power-constrained batteries built into sensors, which significantly affects the WSN lifetime. The uneven geographical structure causes multiple random paths to be followed in data collection. However, due to constrained battery power capacity and ecological variations, power utilization is a tricky issue in WSN. The work done in this paper proposes an efficient data collection mechanism in Mobile Sink WSN using reinforcement learning in order to address battery power constrain in WSN. The proposed model uses Q-Learning approach that induces automatic learning through the shortest path for data collection. The outcomes of the proposed model's experiment show it works much better as compared to the existing model.

Keywords: WSN, Q-Learning, Mobile Sink, Reinforcement Learning.

I. INTRODUCTION

The Mobile Sink Wireless Sensor Networks (MSWSNs) uses mobile device to gathering data from sensor nodes in WSN. The MS-WSN offers several advantages in energy efficiency and data gathering flexibility compared to static sink networks. The WSN comprises a number of battery-powered interconnected sensors which communicate with each other [1]. The WSN is attracting researchers' because it has become key technology for Internet of Things (IOT) and plays an important role to transmit and receive data wirelessly. The Mobile Sink in WSN is one of the most important things for data collection. Many researchers have been proposed various data collection mechanism through MSs in WSN [2].

Sending sensory information through relay often causes a hot spot problem with a stationary sink in the WSN, and sensors nearby are affected to the sink exhausts their energy rapidly. On contrary of this, the MSs in WSNs gather sensory information sent from the sensors straight or through fewer relays. The MS can move through the network, which saves a significant amount of energy and achieve longer lifetime. The MSs have ability to accessing data in disconnected WSNs that is very useful for deployment of a sparse WSN [3].

The traditional WSN used dense arbitrary matrix as observation matrix to compress and collect data in wireless sensor network through the compressed sensing methods. However, each projection value requires all nodes in the network to take part in the operation, leading to dense observation issues within a dense measurement matrix [4]. Reconstructing the signal demands a large amount of computation, and gathering the projection values involve significant communication overhead. The sparse matrix gathers measurement data from certain nodes in the network to generate the projection value. The gathered measurement data lowers communication costs between nodes and reduces the number of calculations needed to construct the projection value. [5].

The sensors are main source of data transmission and reception and sources of energy consumption. An efficient mechanism is required to control and manage energy consumption to design power attentive routing protocols for WSN [6]. The poor energy consumption mechanism in many-to-one traffic scheme results in energy loss and destruction of energy resource known as energy-hole problem. The best possible path frequent selection and energy-hole problem mutually impact on the routing algorithms life time of WSN. The network will be partitioned due to both problems, and WSN will not be able to complete intended critical function. Such kind problems in routing protocols reduce energy utilization at outlay of non-uniform energy drainage in the network [7].

WSN lifetime is a challenging issue, affects on the network performance, the WSN lifetime should be high for the better performance of the network; therefore, during design of the WSN protocol the lifetime should be considered. The parameters i.e. energy consumption, load balancing, path selection, and packet transmission which affects of WSN lifetime should be considered during design of WSN protocols [8].

A. Motivations

There are certain drawbacks of traditional WSNs which are presented here. Majority of the existing WSNs considered only residual energy not to other factors in selection process of the cluster head. Most of the data in WSN and IoT environments is forwarded by the cluster heads that are close to the sink node. The cluster heads near the sink nodes create an energy-hole problem due to fast energy lose as compared to the cluster heads far from the sink nodes. Earlier proposed data transfer mechanisms for multi-path routing in WSNs did not achieve an efficient data transfer mechanism. However, the way data is sent in Wireless Sensor Networks (WSNs) can be enhanced to extend the lifespan of the network. Previous work did not completely examine the best route selection mechanism for mobile devices. Subsequently, the range of data gathering mechanism used for WSNs and IoTs may be extended using reinforcement learning techniques.

II. RELATED WORK

Sensors in WSN communicate over wireless links within limited transmission range to send or receive data. Energy consumption over wireless linked system corresponds to a significant portion of total energy consumption at sensor levels [9]. The sink's neighbour nodes represent bottleneck of the network lifetime. These are heavily overloaded due to funnelling effect in muli-hop transmission in WSN. The researchers have overcome the funnelling effect in recent studies using of Mobile Sinks (MSs) to collect data in WSNs [10].

Mobile Sinks (MSs) have limited energy resources and move across the sensing field to gather data from sensors through short-range communication links before transmitting the collected information to a remote centre.The long-hop communication needs high power; therefore, it is not used in WSN.

The MSs should traverse the sensing field timely and efficiently to collect data from the sensors, because failure visit of the some parts of sensing field will leads to data loss; and frequent visit of sensing areas will result in data delivery delay [11].

The MSs is an effective mechanism to relieve traffic load from a precise set of nodes that improves system performance in WSN [12]. Three types of mobility model such as random, controllable, and constrain can be found in the recent research works on WSNs with MS. The random mobility model is simple mobility model that applies random walk-in sensing area to gather information from sensors nodes [13].

Since, randomness causes in random mobility model is difficult to bind the collecting latency and data delivery ratio. The controllable mobility mechanism is applied in the controllable mobility model; where MSs freely moves in the sensing area and visits all or some parts of sensor nodes to collect data from the sensors [14]. Some time it is not possible to implement the random and controllable mobility model for MSs in WSN then constrain mobility model is used in which MSs are attached to vehicles for predefined trajectories [15].

Sometimes, planned trajectory cannot be realized in the urban areas because of the MSs are constrained to roads. Alternatively, by mounting MSs on the vehicles like buses can be avoided some difficulties and can provide better performance for data collection [16].

Since, buses are already a component of the environment and follow predefined routes. Therefore, the difficult path planning and complex movement control of MSs can be avoided [17]. Exploring each sensor node separately is a time consuming due to low speed of MASs, and multi-hop communication with constrained path the MSs increased data delivery delay [18].

The MSs collects data either through single hop or multi-hop communication. A number of data collection approaches have been proposed using trajectory constrained mechanism in recent years [19].

The authors installed MSs on bus that has to follow fixed route and moves periodically to collect data from sensors installed near the route. A queuing formulation process is used in this model to collect data and shown that predictable mobility leads to large energy saving over convention static WSNs [20].

The most of researchers used either single hop or multi-hop communication based on flat network structure. The data aggregation in large scale WSN necessitates an efficient organization of the network topology for balancing the load and prolonging the network lifetime [21].

III. PROPOSED MODEL

The current communication landscape demands sophisticated infrastructure capable of delivering highly efficient and reliable quality of service. Information and Communication Technologies (ICT) incorporates advanced technological frameworks to support modern connectivity requirements. Nowadays, combination of WSNs and IoTs widely uses for environmental monitoring tasks.

The sensors are deploying at random in the network, and network is divided into several clusters. The sensor with high energy level is chosen CH and rest of sensor works as member of cluster. The member nodes of cluster send information to CH; and CH delivers data to the base station using data transmission mechanism.

The following implementations are considered to design the proposed model: (i) all sensor nodes are homogeneous and have same energy level, (ii) same operation ability of data processing such as data sensing and receiving, (iii) it is assumed that there is no obstacles present in the region. The symbols used in this proposed model are described in Table 1.

TABLE 1
USED SYMBOLS

Notation	**Description**
X	Sensor nodes set, $X = \{x_1, x_2, x_3, \dots, x_k\}$.
C	Cluster heads set, $C = \{CH_1, CH_2, CH_3, \dots, CH_l\}$, $l \leq k$.
CH	Cluster Head
nCH	Total CHs
N	Sensor network modeled as a graph
Z	Random parameter applied in the LEACH algorithm
V	Graph vertices set
E	Graph edges set
R	Reward function
S	Q-Learning set space
A	Actions in Q-learning
qM	Queue matrix stores Q-values

A. Energy Model

The built-in battery in the sensors is the key source of power supply in the network, and there is no option to get recharge battery time by time. Here a radio model is taken on for data sending and receiving in the network. Energy is primarily consumed during data transmission through the operation of the radio circuitry and the energy amplifier. The amount of power is needed to transmit *a* b bit on a remoteness *d* is expressed as:

$$E_{tr}(b,d) = \{E_{tm}.b + k_{fs}.b.d^2 \; for \; d \leq d_0 \; E_{tm}.b + k_{fp}.b.d^4 \; for \; d > d_0 \quad (1)$$

Where, E_{tm} represents transmission power that is needed to send data on a wireless medium, the energy utilization in free-space model is represented by K_{fs}, and the energy utilization in multi-way model is shown by K_{mp}. The power needed by the recipient to gather *b* bits.

$$E_{rc}(n) = E_{tm}.b \quad (2)$$

Where, E_{rc} represents to energy that is needed to take delivery of data over a wireless communication link.

B. Network Model

Below Fig. 1 shown network model that contains sensor nodes and MS. The MS have limitless power and it can travel everywhere in the network. The MS used Q-Learning to the finds best path in the network for data collection. The base station (BS) supply location of CH to MS and executes the Q-Learning mechanism to decide the optimal path. The MS has sufficient memory space to accumulate data gathered from the CHs and handovers collected data to BS. The network life span is the period until the last node in the sensor network stops working because of the use of MS.

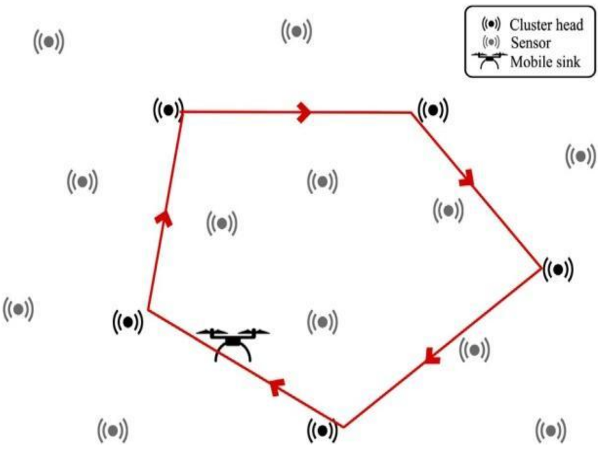

Fig. 1.Mobile Sink Network Model

C. Proposed RL Technique

In this model, the Reinforcement Learning (RL) technique maximizes the agent's reward by choosing a series of actions based on communications with the environment. The environment is represented by the Cluster Heads (CHs), while the MS functions as the agent responsible for decision-making. The steering surroundings starts by sending the next CH position to the agent MS, and required action is taken from the state information, and the resultant reward will be given. The Fig. 2 showed the elementary RL model for the IoT-based WSN environment monitoring.

A sensor network can be represented as a graph N=(V,E), where each sensor node or CH corresponds to a vertex Vi and Vj, and each edge Eij enables bidirectional communication between node pairs Vi and Vj. Let s ∈Vs denote a source node, while D ⊂ V indicates a set of destination nodes. Determining the least-cost route from the source to all goal nodes in D is referred to as multi-destination routing. The Q-Learning R = (VR, ER) algorithm determine the shortest route with vertices include source and destination nodes. If MS covered all destinations, then the cost of a path R would be lesser it results in fewer travel remoteness and more benefits.

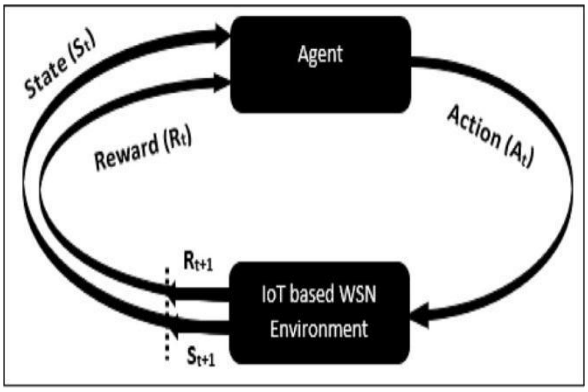

Fig. 2. Reinforcement Learning

D. Clustering

The improved LEACH algorithm works in two main stages for grouping: the setup stage and the steady-state stage. In the setup stage, sensor nodes are placed in the area, groups are formed, and leaders for each group, known as cluster heads (CHs), are chosen. Each node uses a certain amount of energy based on where it is located, what it needs to do, and how it monitors the surroundings and sends data. The way energy is used up depends on how far the data travels most of the time. In the steady-state phase, every CH gathers data from its member nodes, combines the data, and sends the processed information straight to the destination. This transmission uses a time division multiple access (TDMA) method, where equal time slots are set up in a round-robin order. Every sensor node is given a random number that falls between 0 and 1. A node becomes the CH, when its value goes below a set limit. The clustering process keeps going in cycles while the network is working until the last sensor node stops being active. Algorithm 1 gives a clear explanation of how the cluster head is chosen Algorithm1 Cluster Formation

a) Input: Sensors (X)
b) Output: Cluster heads (CHs) and its coordinates

E. Routing

Once the clusters are formed, the Base-Station (BS) gets the location of all the CHs. A Reinforcement Learning (RL) method is used while gathering data to find the most excellent routing path that works most efficiently. The route information that was figured out is sent to the Mobile Sink (MS), allowing it to go to each Cluster Head (CH) and collect the necessary data. To lower energy use and cut down on the time it takes to send data, each Cluster Head uses data fusion methods to make the packet size smaller before sending information to the Mobile Station. When the MS gets within the communication area of a CH, it sends out a ready-to-receive signal. The CH then replies with an acknowledgment (ACK) message to confirm that the data transfer was successful. After finishing the data collection from the current CH; the MS moves on to the next CH on the route. In reinforcement learning, we consider cluster heads as states. The agent, which is a software program that makes decisions, finds the quickest path by choosing a series of actions (a) through various situations (s) while earning rewards (R). In the beginning, when learning, the RL algorithm does not recognize the most excellent action to execute for each situation. As time goes on, it gets better at focusing on actions that create the quickest and most effective route.

RESULTS

The suggested model is put into action and tested through MATLAB simulations to check how well it works overall. Three different situations are looked at: the first one studies traditional methods for clustering and routing in WSNs and the Internet of Things (IoT); the second one looks at a strategy that uses a Mobile Sink (MS) for clustering and routing; and the third one compares the suggested method with the best current methods based on various network performance measurements.

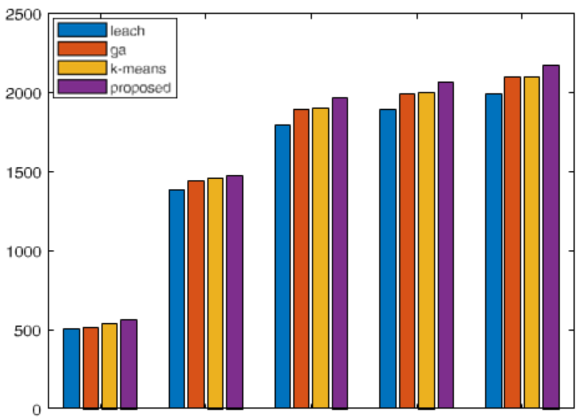

Fig. 3. Death of initial node

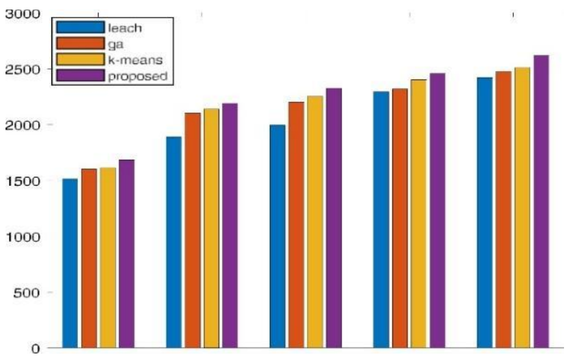

Fig. 4. *D*eath of last node

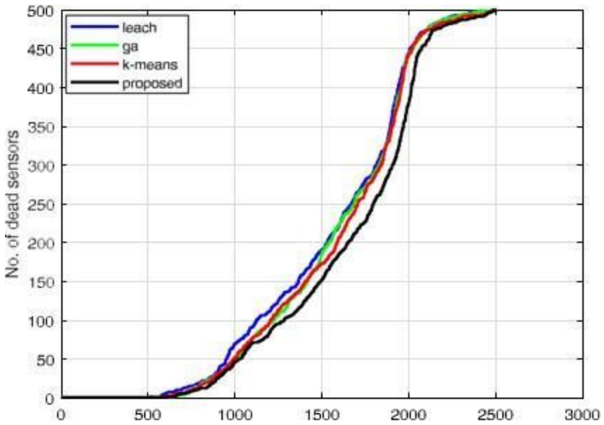

Fig. 5. *D*eath of last node

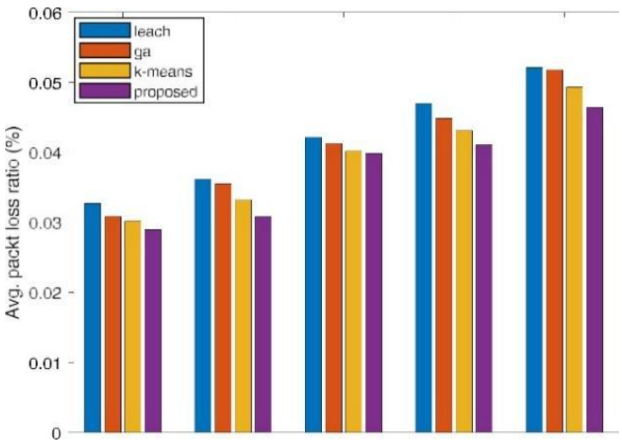

Fig. 6. Average packet loss in (%).

The life span of the network is affected by the condition of the initial nodes. The last nodes are presented in Fig. 4 and 5 respectively. From Fig. 4 and 5, we can observe in the figures that the suggested solution holds a higher level of effectiveness such as lifespan of the network when compared to other traditional systems is much high. The reason for the longer life of the network is the substitute of conservative data communication method by the MS strategy. To move the data, the majority of the sensor nodes choose one-hop communication to send their data to the corresponding CH. Additionally; the suggested Q-Learning method actively looks for the quickest path compared to all the CHs that can be used to do data work collection. So, we see that the mix of MS and. Q-Learning methods help to extend the lifespan of the network.

IV. CONCLUSION

A Q-learning framework based on reinforcement learning is presented to allow automated routing by using a MS for gathering data. At first, a better way of grouping is used to find the main nodes in WSN that are part of Internet of Things (IoT) settings. After that, a Q-learning algorithm is used to find the best path for collecting data. In this setup, traditional methods of sending data are changed to the Mobile Sink method, which lets data be sent to the Base Station (BS) in a single hop. This method greatly reduces the amount of energy that sensor nodes use. Also, combining clustering, the movement of mobile sinks and reinforcement learning helps create a more self-sufficient and energy-saving wireless sensor network design, which ultimately increases the total lifespan of the network. To check how well the suggested method works, several test situations are studied and compared with current techniques. The method is also tested with different learning-factor values to find a suitable reward system for the Q-learning process. Future studies might include things like how nodes move, barriers in the environment, and noise in communication channels to make the models more realistic. Also, broadening the framework to include several mobile sinks and looking at different Q-learning methods could give us a better understanding of how well RL works in IoT systems that use wireless sensor networks.

REFERENCES

[1] Al-Rawi,H.A.A.,Ng, M.A.,Yau,K.-L.A., 2015.Application of reinforcement learning to routing in distributed wireless networks: a review. Artif. Intell. Rev. 43 (3),381–416.

[2] Al-Sodairi, S., Ouni, R., 2018. Reliable and energy-efficient multi-hop LEACH-based clustering protocol for wireless sensor networks. Sustain.Comput.:Inform.Syst.20, 1–13.

[3] Alsheikh, M. A., Lin, S., Niyato, D., Tan, H., 2014. Machine learning in wireless sensor networks: Algorithms, strategies, and applications. IEEE Commun. Surv. Tutor. 16(4), 1996–2018.

[4] A.M., K., Hu, F., Kumar, S., 2018. Intelligent spectrum management based on transfer actor-critic learning for rate less transmissions in cognitive radio networks. IEEET rans. Mob. Comput. 17 (5), 1204–1215.

[5] Bandyopadhyay, D., Sen, J., 2011. Internet of Things: Applications and challenges in technology and standardization. Wirel.Pers.Commun.58(1),49–69.

[6] Bello, I., Pham, H., Le, Q.V., Norouzi, M., Bengio, S., 2016. Neural combinatorial optimization with reinforcement learning. CoRRarXiv:1611.09940.

[7] Charrada, estimation in Commun. 10 (17), 2435–2444.

[8] Chen, H., Li, X., Zhao, F., 2026. A reinforcement learning-based sleep scheduling algorithm for desired area coverage in solar-powered wireless sensor networks. IEEE Sens. J. 16 (8), 2763–2774.

[9] Cheng, S.-T., Wu, M., 2009. Optimization of multilevel power adjustment in wireless sensor networks. Telecommunication. Syst. 42(1),109–121.

[10] Dietrich, I., Dressler, F., 2009. On the life time of wireless sensor networks. ACM Trans. Sen. Netw.5(1),5:1–5:39.

[11] Dong, M., Liu, X., Qian, Z., Liu, A., Wang, T., 2015. Qoe-ensured price competition model for emerging mobile networks. IEEE Wirel. Commun. 22(4), 50–57.

[12] Donta, P .K., Rao, B.S.P., Amgoth, T., Annavarapu, C.S.R., Swain, S., 2020. Data collection and path determination strategies for mobile sinkin 3DWSNs.IEEESens. J. 20 (4), 2224–2233.

[13] Fanian, F., Kuchaki Rafsanjani, M., 2019. Cluster-based routing protocols in wireless sensor networks: A survey based on methodology. J. Netw. Comput. Appl. 142,111–142.

[14] Fu, X., Yao, H., Postolache, O., Yang, Y., 2019. Message forwarding for WSN assisted opportunistic network in disaster scenarios. J. Netw. Comput. Appl.137,11–24.

[15] Gantassi, R., Gouissem, B. B., Othmen, J. B., 2020. Routing protocol LEACH kusing K-means algorithm in wireless sensor network. In: Barolli, L., Amato, F.,Moscato, F., Enokido, T., Takizawa, M. (Eds.), Web, Artificial Intelligence and Network Applications. Springer International Publishing, Cham, pp.299–309.

[16] Gu,Y., Ji, Y., Li, J., Zhao, B., 2013. ESWC: Efficient scheduling for the mobile sink in wireless sensor networks with delay constraint. IEEE Trans. Parallel Distrib.Syst.24 (7), 1310–1320.

[17] Gu,Y., Ren, F., Ji, Y., Li, J., 2016. The evolution of sink mobility management in wireless sensor networks: Asurvey. IEEE Commun. Surv. Tutor. 18(1),507–524.

[18] Gupta, S. K., Jana, P. K., 2015. Energy efficient clustering and routing algorithms for wireless sensor networks: G A base dapproach.Wirel.Pers.Commun.83(3),2403–2423.

[19] Gupta, G .P., Saha, B., 2020. Load balanced clustering scheme using hybrid metaheuristic technique for mobile sink based wireless sensor networks. J. Ambient Intell. Humaniz. Comput..

[20] Habib, M. A., Saha, S., Razzaque, M.A., Mamun Or-Rashid, M., Hassan, M.M., Pace, P., Fortino, G., 2020. Lifetime maximization of sensor networks through optimal data collection scheduling of mobile sink. IEEEAccess8,163878–163893.

[21] He, Y., Yu, F., Zhao, N., Leung, V., Yin, H., 2017. Software-defined networks with mobile edge computing and caching for smart cities: A big data deep reinforcement learning approach. IEEE Commun. Mag.55 (12),31–37.

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