DESIGN AND ANALYSIS OF ENERGY EFFICIENCY IN HYBRID IOT-WSN USING MACHINE LEARNING ROUTING

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Abstract

Wireless Sensor Network (WSN) based on the Internet of Things (IoT) provides more flexibility and reduces network deployment and enjoys a problem of power balance between the sensor nodes because IoT operates primarily on fixed devices or sensors, while WSNs operate on mobile sensor nodes. Thus it becomes increasingly difficult to choose efficient and short paths through the WSN Protocol or it may lose focus on selecting the shortest possible route. Consequently, correct use of battery power in a multi-hop transmission is necessary to maintain network connectivity. This article uses IoT-WSN routing from the Artificial Neural Network (ANN). IoT nodes help in data collection and acquisition and WSNs route data and effectively transmit packets between the source and the sink nodes. In terms of mean energy efficiency, delay and network efficiency the simulation results are estimated. The ANN results are more network-wide than the existing machine learning algorithm.

Keywords:

Machine Learning, Wireless Sensor Networks, Routing, Energy Efficiency

1. INTRODUCTION

In recent times, clever cities have emerged as broad, smart, and open environments, enhancing IoT research standards as an integral part of the daily lives of citizens [1] [2]. To this end, the data collected from the intelligent [10]-[12] objects, which are highly integrated in the sensing capability, is continuously collected, compiled and monitored. In order to address the open and dynamically unpredictable unusable conditions in different environments [2]-[5], this activity provides vital standardisation.

A relevant objective for new, self-sustaining and adjustable services for smart cities is to cover several different applications, ranging from environmental monitoring and habitation to security monitoring and user support for city life and roaming [6]. The latest wireless communication and mobile devices [7]-[9] are opening up these new services with new integration opportunities. In order to solve this effect, the proposed method uses an ANN algorithm that helps the standardisation of routing protocols on the basis of the IoT sensor node input data.

In general, machine learning is defined as a set of instruments and algorithms used to construct prediction models by sensor network designers. Yet specialists in the area of machine learning consider it as a rich field with very wide themes. Understanding those concepts can benefit people who want to implement WSN machine learning. Machine learning algorithms deliver significant versatility advantages for various WSN applications. This section presents some of the theoretical principles and techniques for integrating machinery learning in WSNs.

The composition of the model may be classified by current machine learning algorithms. Most of the machine learning algorithms fell into the supervised, unattended and improved learning categories. A named training data collection is given with machine learning algorithms in the first group. The system model describes the relationship of input, output and system Parameters. This set is used to construct the system model. Unlike supervised learning, labels do not contain supervised learning algorithms (i.e., there is no output vector). Fundamentally, the purpose of an unattended learning algorithm is to identify sample sets by observing the similarities of the input samples into various classes (i.e. clusters). In category three the agent learns by interacting with his environment by using enhancement learning algorithms (i.e., online learning). Finally, certain learning algorithms naturally do not fall into this group since both controlled and unattended learning methods share characteristics. These hybrid algorithms (usually termed semi-controlled learning) seek to gain the strengths and weaknesses of these main categories.

The principal contribution is: the study proposes to route IoT-WSNs through the ANN. The IoT nodes collect the input data, and WSNs route the data to sink nodes effectively. In terms of mean energy efficiency, delay and network efficiency the simulation results are estimated.

2. PROPOSED METHOD

Opportunistically, our WSN-IoT integration uses clusters through WSN, which tend to function quickly with the data transfer. This makes it faster and works more robustly, which is entirely dependent on a single hop and limited speed transmission. The clustering protocol is reactively initiated by each WSN node named CH, which snoops on an immediate IOT route data packet. The protocol consists of three phases. In the first stage, the CH removes the IOT node gradients that have routed it from the data packet, thereby sending a two-hop limited request for additional IoT nodes and asking them to join a new cluster. The second step involves sending a discovery message to the IoT so that it communicates and transmits the Join request to the cluster. The sensor nodes of WSNs are capable of communicating to the cluster with the IoT input nodes. The sensor nodes in WSNs submit an application for a connection in a cluster where the nodes are selected by ANN on the basis of their energy level and routing capacity. In the third and final phases, WSN nodes communicate with CH. The CH collects responses from the nodes of the cluster and then selects an optimised gradient sensor node as the exit point. Collecting the answers from all the cluster nodes allows CH's numerous messages, which are exchanged by WSN and IOT: appropriate policy can determine the length, ensuring their energy demand.

Different design challenges such as energy use, failure tolerance, scalability and data coverage have to be considered when designing a WSN routing protocol. Limited processing capacity, small memory and low bandwidth are provided for sensor nodes. In wireless sensor networks it is traditionally possible to create a routing problem as Graph $G = (V)$ where V is a set of all nodes and E a set of two-way communication channels that connect the nodes. This model helps one to describe the routing problem as the method of seeking a minimum price path from the source vertex and across the available graph boundaries to all destination vertices. This path in fact covers a tree $T = (V, E)$, which has a root node and a source at the vertices (i.e., leaf nodes that do not have any child nodes). Even when the full topology is known, solving such a tree with optimum information aggregation is NP-hard.

The distributed framework relies on network nodes to match its own measurement to a global function. The nodes are used as weighted components to execute a kernel linear regression. Kernel functions map the samples in certain function rooms to facilitate data handling (refer to for an introduction to kernel methods). The frame proposed takes advantage of the high correlation between the measurements of multiple sensors. This minimises the overhead communication to detect the sensor data structure. These results are collectively a major step in developing a distributed wireless network learning framework using linear regression methods. The main advantages of using this algorithm are the good results and the little overview of the study phase. But nonlinear and complex functions could not be learned.

Recently, the WSN research community has dealt with the design of effective event detection and query processing solutions. The simplest techniques rely on defining a strict phenomenon threshold value, which makes the system manager alarmed of any breaches. However, events and query processing units are often complicated in more recent implementations of WSNs and require more than a predefined threshold value. One of these emerging techniques is the development of advanced event detection and query processing solutions through machine learning.

The development of effective event detection mechanisms with limited storage and computing resources needs is made possible by learning algorithms. They also can use simple classifiers to evaluate the accuracy of such events. Machine learning helps to develop effective WSN query processing techniques to determine the areas of search when a query is received without inundating the entire network.

2.1 ARTIFICIAL NEURAL NETWORK ROUTING

The ANN is a probable generative model designed to consist of several stochastic hidden layers over one single observed input layer of variables representing the input data vector in deep neural network (DNNs). DNNs have undirected connections between the direct connection and the top two layers to all other layers at the level above. There is an effective and uncontrolled algorithm to learn how weights can be combined in a DNN, which is the training for the adjacent pair of layers of a limited Boltzmann machine (RBM). The DBN algorithm uses its hidden units to decide the sensor node states and the conditions are determined by a data vector.

For initialising weights, the pretraining algorithm uses the DBN weighs and then uses a forward feed algorithm to adjust weights. The stochastic downgrade after pre-training with the Random Initialization of Deeper Architecture, for the formation of the Artificial Neural Network, helps to train robust random seeds, with often superior results. Even with high capability models, the models prevent overlap during pretraining and can then help optimise the weight of the recognition.

3. RESULTS AND DISCUSSIONS

In this section, we present an IoT-WSN routing cluster and compare it to the routing algorithm of the learning machine. The delay, energy efficient and transmission rate of the cluster-based network routing compares machine learning with or without the cluster.

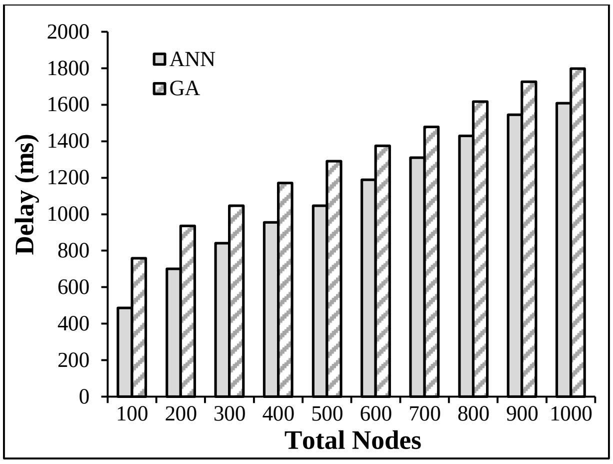

Fig.1. Delay without clustered routing

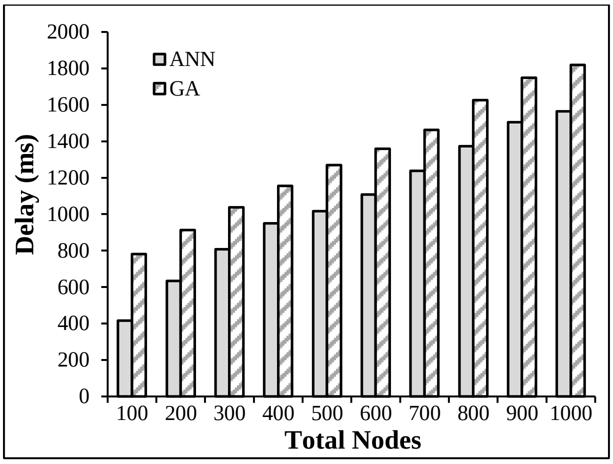

Fig.2. Delay with clustered routing

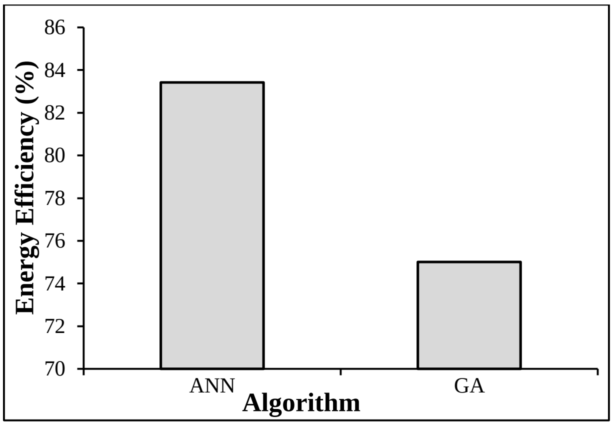

Fig.3. Energy Efficiency without clustered routing

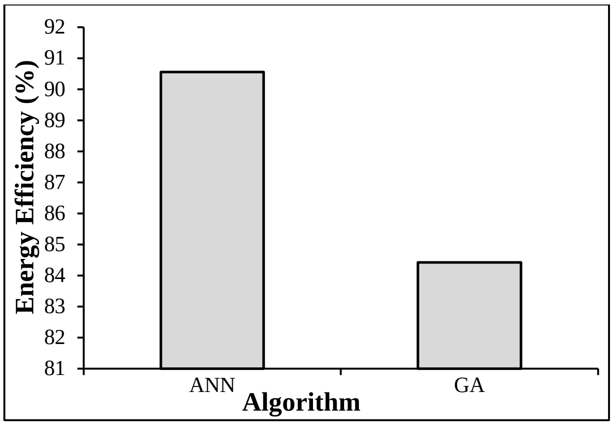

Fig.4. Energy Efficiency with clustered routing

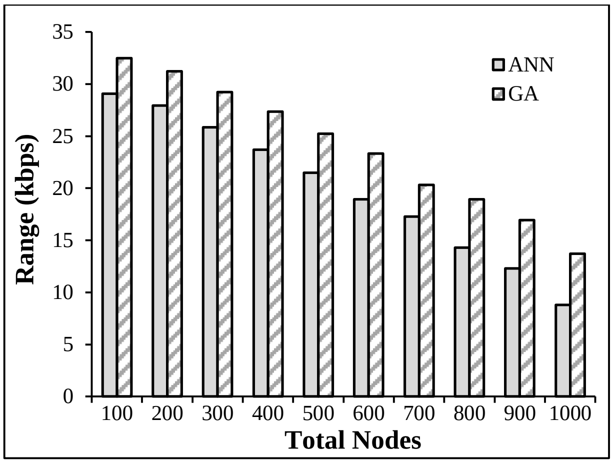

Fig.5. Transmission rate without clustered routing

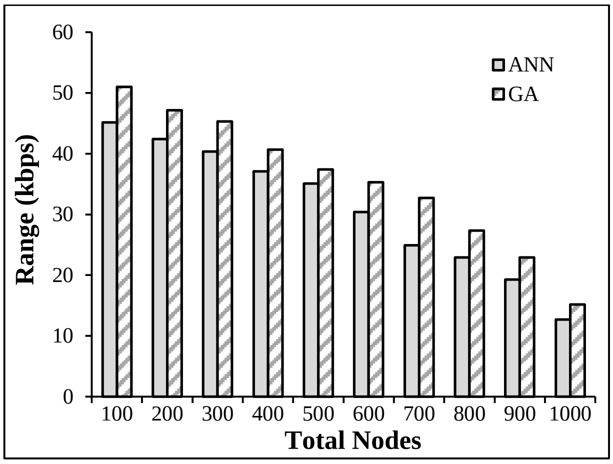

Fig.6. Transmission rate with clustered routing

The Fig.1 and Fig.2 show the delay between the deep learning proposed and existing machinery-based routing algorithm. The Fig.3 and Fig.4 show the energy efficiency between the proposed deep study and the existing machine-based routing algorithm. The Fig.5 and Fig.6 show the transmission rate between the proposed machine learning and existing Cluster-based Learning algorithms.

The results of the delay show that the proposed method is less delayed than without the cluster-based routing. The proposed method, by contrast, results in less delay than machine learning algorithms in the proposed machine learning algorithm. Energy efficiency results show that with cluster-based routing, the proposed method achieves increased energy efficiency as without cluster-based routing. The transmission rate results show that the proposed method increases the energy efficiency with cluster-based routing as it does without cluster-based routing. On the other hand, the proposed method is based on the deep learning algorithm, which achieves increased energy efficiency as the transmission rate. The proposed method, however, is an enhanced rate of transmission compared to machine learn algorithm by the proposed deep learning algorithm.

The study proposed now reveals that the cluster-based routing achieves a greater QoS than the routing algorithm for the machine. The routing on a cluster provides greater routing capacity than without cluster approaches.

4. CONCLUSIONS

In this paper the ANN routing for IoT-WSNs is a machine learning routing proposal. The collection and data acquisition of the IoT nodes is undertaken and data routing, and WSNs are responsible for the efficiency of data transfer from source nodes to sinks. The results are analysed with average time, network and throughput. The results of the simulation. This results in a higher network of the method of deep education than the existing algorithm.

REFERENCES

[1] K. Li, H. Huang, X. Gao and F. Wu, “Qlec: A Machine-Learning-based Energy-Efficient Clustering Algorithm to Prolong Network Lifespan for IoT in High-Dimensional Space”, *Proceedings of 48th International Conference on Parallel Processing*, pp. 1-10, 2019.

[2] N. Youssry and A. Khattab, “Ameliorating IoT and WSNs via Machine Learning”, *Proceedings of IEEE International Conference on Microelectronics*, pp. 342-345, 2019.

[3] A. Sathesh, “Optimized Multi-Objective Routing for Wireless Communication with Load Balancing”, *Journal of Trends in Computer Science and Smart Technology*, Vol. 1, No .2, pp. 106-120, 2019.

[4] W.H. Hassan, “Current Research on Internet of Things (IoT) Security: A Survey”, *Computer Networks*, Vol. 148, 283-294, 2019.

[5] Y. Mekonnen, S. Namuduri, L. Burton and A. Sarwat, “Machine Learning Techniques in Wireless Sensor Network based Precision Agriculture”, *Journal of the Electrochemical Society*, Vol. 167, No. 3, pp. 37522-37529, 2019.

[6] R.K. Poluru and S. Naseera, “A Literature Review on Routing Strategy in the Internet of Things”, *Journal of Engineering Science and Technology Review*, Vol. 10, No. 5, pp. 1-13, 2017.

[7] Z. Abbas and W. Yoon, “A Survey on Energy Conserving Mechanisms for the Internet of Things: Wireless Networking Aspects”, *Sensors*, Vol. 15, No. 10, pp. 24818-24847, 2015.

[8] I.A. Najm, A.K. Hamoud, J. Lloret and I. Bosch, “Machine Learning Prediction Approach to Enhance Congestion

Control in 5G IoT Environment", *Electronics*, Vol. 8, No. 6, pp. 607-614, 2019.

[9] W. Twayej and H.S. Al-Raweshidy, "M2M Routing Protocol for Energy Efficient and Delay Constrained in IoT Based on an Adaptive Sleep Mode", *Proceedings of SAI Conference on Intelligent Systems*, pp. 306-324, 2016.

[10] J. Zhang, F.Y. Wang, K. Wang and W.H. Lin, "Data-Driven Intelligent Transportation Systems: A Survey", *IEEE Transactions on Intelligent Transportation Systems*, Vol. 12, No. 4, pp. 1624-1639, 2011.

[11] J. Zeyu, Y. Shuiping, Z. Mingduan and C. Yongqiang, "Model Study for Intelligent Transportation System with Big Data", *Procedia Computer Science*, Vol. 107, pp. 418-426, 2017.

[12] N. Youssry and A. Khattab, "Ameliorating IoT and WSNs via Machine Learning", *Proceedings of International Conference on Microelectronics*, pp. 342-345, 2019.