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ANALYSIS OF THROUGHPUT IN INTEGRATED IOT-WSN USING MACHINE LEARNING ALGORITHM

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ABSTRACT: The Wireless Sensor Network (WSN) integrated with Internet of Things (IoT) offers greater flexibility in network deployment especially when it is powered with IoT devices. It offers solutions to the energy consumption in between the sensor nodes as the IoT mainly operates mainly as a devices with faster data acquisition. Hence, it is difficult for the sensor nodes to carry such computational burden from the source IoT devices to the target base station or to the internet gateway. It is essential to maintain the routing paths as well as the balance of the sensor nodes. In this paper, we propose a machine learning routing using Artificial Neural Network (ANN) routing on IoT-WSNs is developed to maintain the stable routing path that matches the speed of input data acquisition. The IoT nodes helps in data collection and acquisition and WSNs routes the data collected via hops between the source and sink nodes. The ANN is responsible for controlling the data routing and matches the routing speed with data acquisition speed. Hence, the network is maintained in stabilized condition that integrates both the IoT devices and WSN sensors. The simulation results are estimated in terms of average delay, throughput and network energy efficiency. The result shows that the proposed machine learning method achieves higher network throughout than the existing machine learning algorithm.

KEYWORDS: Machine learning Routing, IoT, WSN, energy efficiency

I. INTRODUCTION

Since last decade, several research efforts have investigated emerging Internet of Things (IoT) applications that allow heterogeneous devices to operate seamlessly in globally integrated communications platforms from smartphones and wireless sensors through to network-enabling physical objects. The new development of intelligent cities, which is conceived as smart, large-scale and open environments capable of enhancing citizens' daily life, further enhances IoT technologies research and related standards as an integral foundation for these new scenarios [1].

For detecting different types of industrial WSN sensor dates in IoT surroundings, sensor interface device is essential. It allows us to collect data from the sensor. We can therefore better understand the information about the external environment. However, the sheer diversity of WSN applications makes increasingly difficult to define “typical” requirements for their hardware and software. In fact, the generic WSN components often need to be adapted to specific application requirements and environmental conditions [3].

However, the acquisition interface can simultaneously collect multiple sensor data to comply mit the requirements of a long-term industrial environmental data collection in the IoT so that more accurate and diverse data can be obtained from the industrial WSN [4] – [8]. These ad hoc modifications have a negative impact on the overall reliability and maintenance, which in turn effectively reduce the use of WSN in IoT applications. [2].

The main contribution of the work involves the following: The authors utilised Artificial Neural Network (ANN) [9] [12]-[14] for carrying out the routing of high speed data packets from IoT on MANETs. The simulation results are conducted in terms of estimated in terms of throughput and network energy efficiency.

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II. PROPOSED METHOD

In areas which require urgent data transmission, WSN-IoT integration uses opportunity-formed WSN clusters. It is simple, robust and depends on a single hop and low speed broadcast. The cluster formation protocol is reactively initiated by any WSN Node called CH which snoops on an IOT route data page. The protocol in Figure 1 contains three phases.

The study uses three phased models:

- Sensing plane,
- Control plane and
- Data plane.

The *sensing plane model* is the collection of multiple IoT devices clusters that collects data from different physical environments.

The *control plane model* consists of ANN model that maintains the routing path by matching the data speeds of input IoT devices.

The *data plane model* helps in routng the packets from the collected IoT device nodes for faster transmission of packets to the destination node.

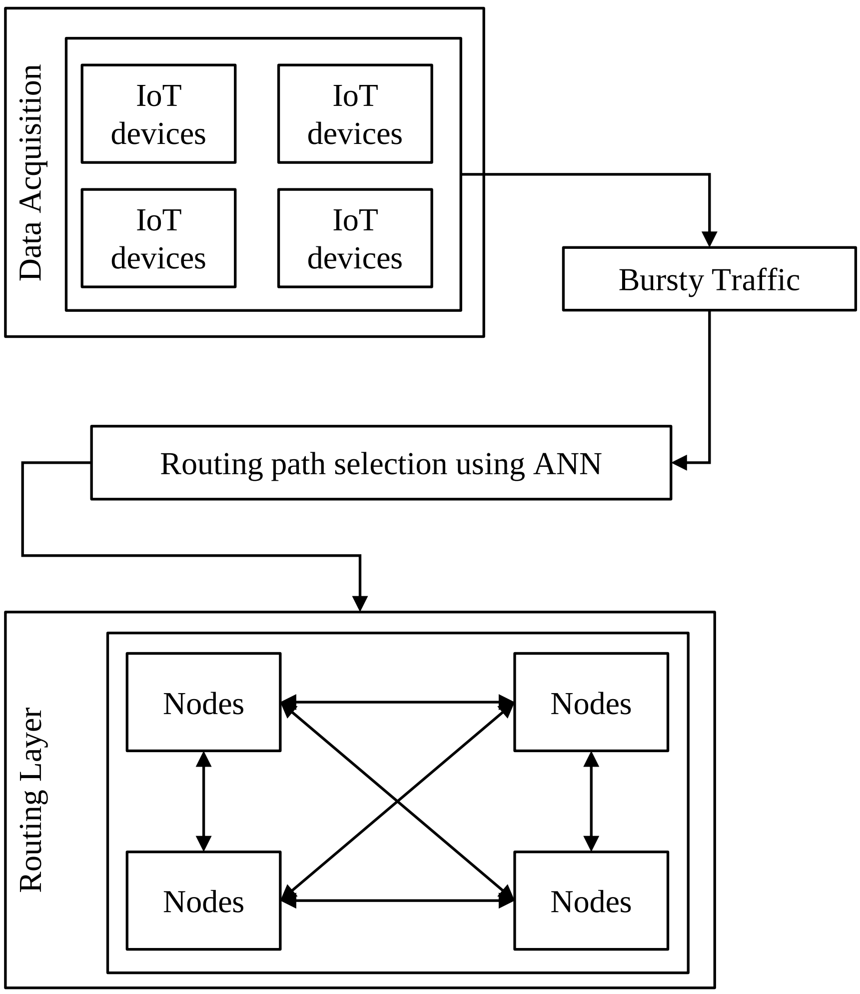

Figure 1: Architecture of IoT-WSN model

In the first stage, the CH removes from the sniffed packet the gradients of the IOT node that routed them and broadcasts a two-hop limitation to request additional knots by asking them to join the new cluster.

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The second stage involves sending a discovery message to IOT to get the best possible gradient between IOT knots they can communicate; then compare this to the gradient that is declared on a Join request: in the cluster, only WSN knots that can communicate better with IOT knots participate.

The WSN Nodes will receive the application for join in the second phase. In the third and last phases of entering the new cluster, WSN nodes communicate to CH. The CH collects the responses from the cluster nodes and chooses to exit the node. By collecting replies from all the cluster nodes, CH can estimate the number of messages exchanged by WSN and IOT: appropriate policies can determine the length and guarantee energy demand for each of them.

III. RESULTS AND DISCUSSIONS

The proposed method is compared with existing methods in terms of various performance metrics that includes: network lifetime, network throughput and throughput. It is compared with Extreme Learning Machine [10] and Reinforcement Learning [11] based routing methods. The entire simulation is carried out with 100 IoT input devices and 1000 sensor nodes.

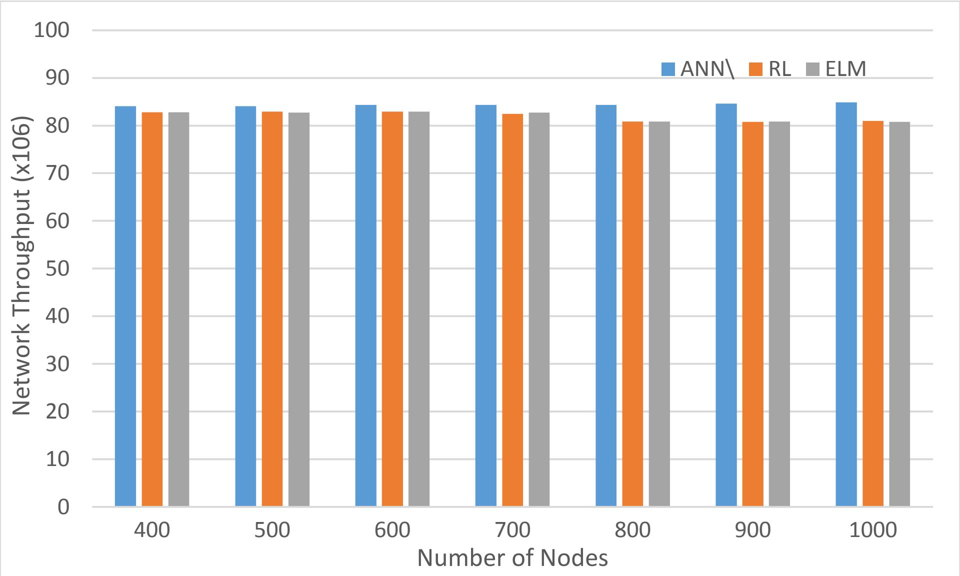

Figure 2: Throughput

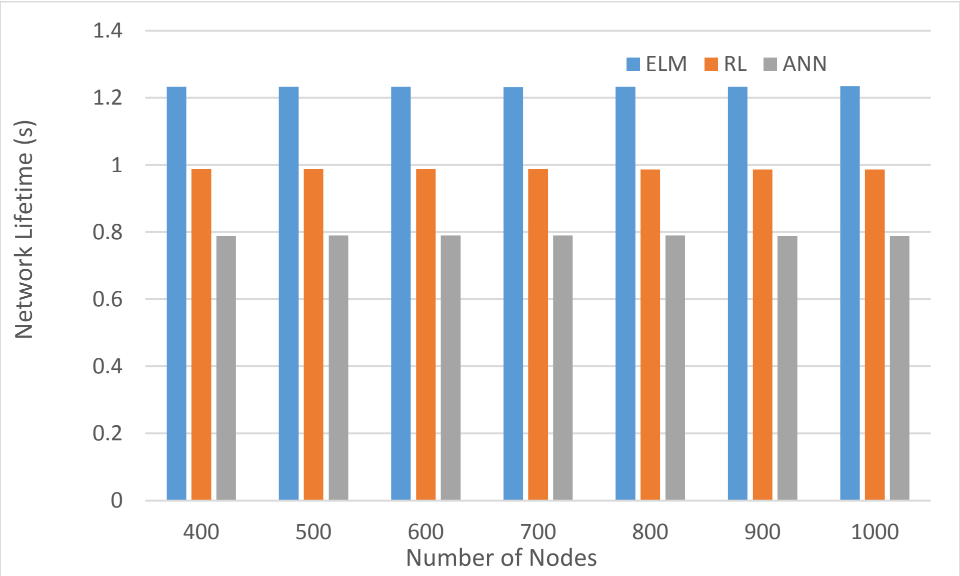

Figure 3: Network Lifetime

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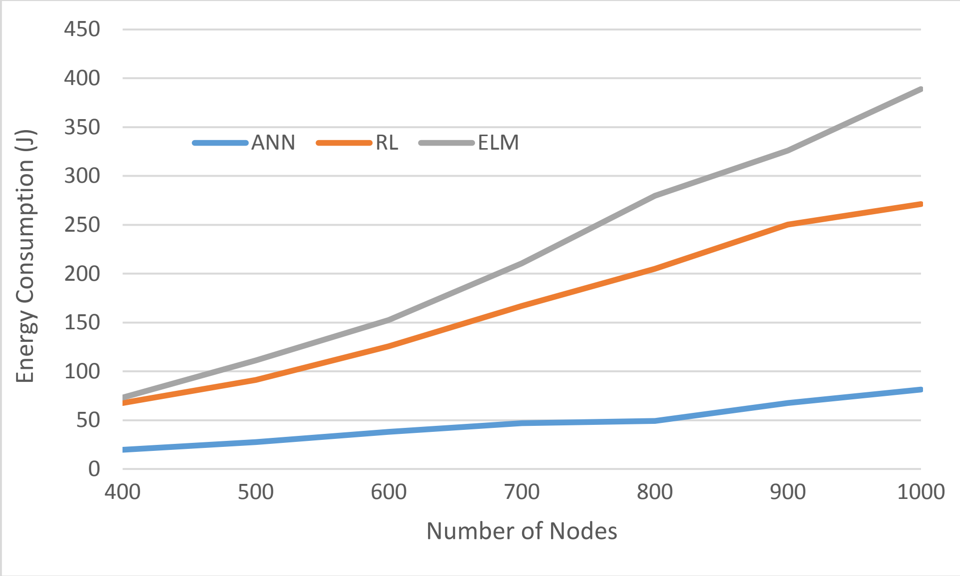

Figure 4: Energy Consumption

Figure 2 shows the results of throughput, figure 3 shows the results of network lifetime and Figure 4 shows the results of energy consumption. Energy efficiency results show that with cluster-based routing the proposed method achieves an increased energy efficiency than without the cluster-based routing. The proposed method, on the other hand, achieves increased energy efficiency by the proposed machine learning algorithm than the machine learning algorithm.

The transmission rate results show that the method proposed achieves an increased energy efficiency by cluster-based routing than by cluster-based routing. The proposed method, on the other hand, is an increased transmission rate than an algorithm for machine learning. The proposed study now reveals that cluster based routing achieves more QoS than the machine routing algorithm through network routing. The routing based on the cluster is higher than without the cluster approach.

IV. CONCLUSIONS

In this paper, ANN routing is established on IoT-WSNs to maintain the high stabilized routing. The ANN controls the routing and matches the routing speed with data acquisition speed. The machine learning in the control phase maintains the WSN in stabilized condition. The study offers greater flexibility while powered with IoT devices over WSN network deployment. The solutions on energy consumption between the sensor nodes are maintained effectively using ANN. The results of simulation shows that the proposed ANN module offer improved balance of network and maintains the scalability of the network.

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