Distance Vector and Prominent Reliable Path Selection based Stochastic Routing in Distributed Internet of Things

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***Abstract*—Delayed delivery of packets hinders the performance of time-sensitive Internet of Things (IoT) applications and incurs increased power consumption. Stochastic routing schemes solve the problem of saving all participating nodes from getting their power drained out quickly. However, stochastic routing incurs the problem of delivery delays and reliable end-to-end delivery. This paper proposes a novel routing scheme, called Q_{ij} routing, to solve these problems. The proposed Q_{ij} routing scheme is a combination of a classic routing scheme, called Distance Vector Algorithm, with a novel re-definition of the cost of a link to find the best path from source to destination. Q_{ij} takes into account the wireless link reliability of any connection between two nodes, and the transmission delay of IoT devices working together in a distributed network. With the presented mathematical model, a routing table is maintained that let an individual node in a network find the distinctly prominent reliable path among many routes from source to destination. The superior efficiency of Q_{ij} routing scheme over eminent stochastic routing schemes is proven through simulation results in terms of reduced end-to-end expected delivery delay and increased expected delivery ratio.**

I. Introduction

An Internet of Things (IoT) system can be defined in several ways. No standard architecture has been agreed upon as a result of any consensus. Similarly, different measures are used to quantify different phenomena in IoT. Reliability is a quantitative measure of the packet delivery ratio from one node to the next intermediate node. Different authors have taken reliability as a quantity representing the serviceability/availability of an IoT system [1]. We consider a very specific type of reliability, i.e., wireless communication link reliability, and explain why a simple, yet so powerful quantitative measure of reliability is needed. The one derived can be used to improve the performance of a network in multiple parameters.

IoT delineates a grid of physical devices inter-connected with each other using Wireless Sensors Networks (WSNs). Advancement in the sixth generation (6G) enables IoT contraptions to become massive, pervasive, and adaptable in a larger number of applications [2]. It is anticipated that the numerosity of IoT devices would exceed 41 billion, producing tens of zeta-bytes of data [3]. To facilitate real-time data processing, adequate transmission of information in a multi-hop fashion is necessary. Traditional routing schemes may not be the right choice for massive IoT (mIoT) when nodes' energy and transmission delay are contemplated [4].

Reliable routing means dependable and timely delivery of important data in critical applications, guaranteeing the arrival of data in an estimated time. Though many packets are lost in connectionless communication, an average uptime guarantee allows a buffer for re-delivery at the cost of less penalty of delay and power consumption. If not properly addressed, this unreliability problem can render numerous distributed IoT applications completely infeasible. The merits of solving the aforementioned problem stochastically instead of deterministically are high. It is because packets are forwarded randomly but prefer one path over another, based on which path satisfies the objective of increasing the delivery ratio or decreasing delivery delay. If a path is frequently traversed by frequent traffic, the nodes maintaining those paths are penalized with quick battery drainage.

Considering the health of a network environment in quantitative analysis shows that links with the ability to throw a packet out of its neighborhood can better provide a reliable path. Another desired quality of selecting the next hop is to minimize the ability to route the packets in its own vicinity. This is ensured by penalizing the probability of choosing a neighbor for the next hop that already has shared neighbors with any node in the role of a decision-maker. It is necessary to choose a neighbor with which the probability of receiving a packet is already higher. Finding the tradeoff between all these is also one of the goals of this research. It is desirable to have the packet traversed across the network in a distributed IoT environment to maximise the end-to-end delivery ratio and minimise the end-to-end delivery delay.

The main contribution of this research is a novel definition of the cost function of a wireless link in a distributed IoT environment. The redefinition of a link's cost considers the very nature of unreliability in quantified mathematical formulation, so that routing decisions can be made on the quantitative analysis.

The rest of the paper is organized as follows. Section II presents a summary of the related work. The network scenario is explained in Section III, along with the proposed scheme for stochastic routing. Results are presented and analyzed in Section IV. The conclusion is presented in Section V.

II. Related Work

The authors of [3] presented an Ordinary Differential Equations (ODEs) based stochastic routing approach. The authors derived the ODEs as limits of Markovian models under the natural escalation in the number of nodes in the network. Although they studied buffer space that affects the faster delivery of the packet, their proposed scheme has high energy consumption, leading to low network continuance. L_{ij} stochastic routing methodology for multi-hop wireless networks was proposed in [5]. The authors show that the packet delivery path was selected on the basis of reliability, but it does not guarantee the optimal path for packet delivery.

A random walk model for stochastic routing in wireless networks was presented in [6]. This study uses two neighbor selection standards that decrease the number of random steps taken to reach the destination. The authors of [7] reduced the packet delivery delay by proposing a novel distributed stochastic routing approach. The authors proposed that the neighbor with the high transition probability and retransmission capability should be chosen as the next hop for packets. A stochastic routing approach, namely, X_{ij} Reliability Expander, was proposed by [8] in order to enhance packet delivery delay and alleviate the delivery delay with unreliable links. This model uses the discrete-time absorbing Markov chains to estimate the packet delivery ratio and delay from source to destination. Although X_{ij} routing scheme performs well compared to the other decentralized methods, X_{ij} tends to choose the longest route because the sender may dispatch out of the neighboring zone.

Markov chain-based model was used by [9] to implement a cost-aware probabilistic model for data collection. The authors used multiple paths from source to destination and the minimum cost is attained by the shortest path from source to destination. The problem of energy consumption and packet delivery delay was addressed in [10] for high-loss WSNs. The authors proposed a new algorithm, Stochastic Optimal Routing Algorithm (SORA), to improve energy consumption and minimize delivery delay. They also compared their model with the other available techniques and showed that SORA outperforms other approaches in terms of energy consumption and delivery delay. The authors in [11] and [12] used the stochastic routing scheme for ad hoc and time-dependent networks. However, energy efficiency is not examined for time-dependent networks, and delay is not considered for the simulation of stochastic routing schemes in ad hoc networks. The authors of [13] addressed the problem of stochastic routing with time-varying uncertainties. The authors proposed a generic speedup scheme known as time-dependent uncertain contraction hierarchies. Their study has shown that time-varying uncertain edge weights can capture data distribution better than real-time traffic conditions.

The authors of [14] have proposed stochastic routing based upon location in an emergency to provide better evacuation communication and execute the rescue operation efficiently. After discovering the paths by performing a random walk on available paths based on GPS data, they assign the bias to the nodes close to the destination. Then all the neighboring nodes are assigned the probabilities which assure the delivery of packets.

The authors in [15], [16] have proposed a Markov model to find the next best node to forward the packet to. Link reliabilities as modeled in [7] is deployed along with [8] but modified the score calculation function to include an additional factor, called the distance ratio. The distance ratio adds a little bias to choosing the neighbors closer to the destination. In this way, among a pool of reliable nodes, the node closer to the destination is selected, thus, minimizing the transmission delay. Choosing the next best neighbor from a set of connected neighbors, using a probabilistic model, is time consuming and computationally expensive.

The authors of [17] proposed reducing previous models' linear and quadratic time complexity to constant time complexity. It is proposed to obtain a probability distribution from the stochastic model and then memorise it using a machine learning model. An implementation of two hidden layers' implementation of a cognitive neural network has been shown to achieve an 82% accuracy of predicting the right node correctly. The dataset used to train the models in [17] is obtained from the stochastic model from [15] and [16].

III. THE PROPOSED Q_{ij} ROUTING SCHEME

The Q_{ij} routing scheme is based on modeling the cost of link in such a way that it takes reliability of a path to be maximized and delay minimized. It does so by keeping the Euclidean distance as short as possible, so that few nodes are traversed automatically.

A. Network Scenario

This section presents an explanation of how a network is modeled. Fig. 1 shows a bunch of randomly distributed nodes in a plane, with coordinates drawn from a random distribution. It is also shown that two farthermost devices are taken as source and sink/destination node with two possible routing paths in the network. There is a possibility of a reliable path in a network that maximizes the probability of sending maximum possible packets without dropping them. Another objective is to reduce the delay. This delay, which is of particular interest here, is usually end-to-end delay and not just internode delay. In the later sub-sections, several parameters will be explained that are important to quantify the probability of selecting the next node. It is desirable for those nodes to be selected which maximize the probability of delivering packets across the path and minimize the end-to-end delay. The proposed routing scheme takes into account four important pieces of information

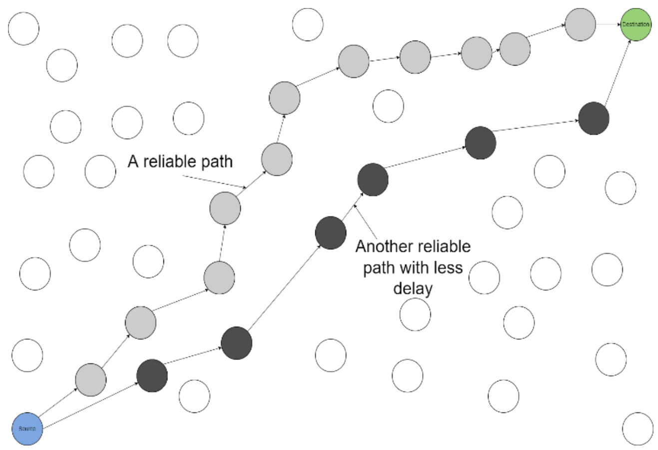

Fig. 1. A network scenario with two possible reliable paths

to calculate the Q_{ij} score of a link between them, and for the links between nodes around them. The four proposed constituents of Q_{ij} score are D_{ij},C_{ij},U_{ij}, and L_{ij}. Details of each factor with mathematical formula for evaluation are given below.

B. The Constitutent Factors of Q_{ij} Score

1) D_{ij}: D_{ij} is the distance between any two nodes, i.e., i and j. In wireless sensor networks, there are multiple ways the distance between any two devices can be found. Among these is the round-trip time sampling, which is given as

$$D_{ij} = c\frac{t_t - t_p}{2} \tag{1}$$

where c is the speed of light which can be discounted depending upon the transmission medium, t_t is the total round-trip time, and t_p is the amount of time taken for processing. For simulation purposes in experimental settings, a simple Euclidean distance is considered as a measure of direct distance between two devices as

$$D_{ij} = \sqrt{(y_2 - y_1)^2 + (x_2 - x_1)^2} \tag{2}$$

2) L_{ij}: Besides the distance, the other observed data is L_{ij}. The rest of the parameters of Q_{ij} score is then derived from those noted L_{ij} scores of a link and other wireless links that exist in that vicinity. L_{ij} score tells us the probability of sending a packet from node i to node j. Quantitively, this data can be obtained by noting how much packets of the sent ones are actually captured at the receiving end. It is, therefore, a ratio of the number of received packets to the transmitted packets. The following formula gives the link reliability

$$L_{ij} = \frac{R_{pkt}}{T_{pkt}} \tag{3}$$

Where R_pkt is the number of packets sent by source, and T_pkt is the number of packets received by destination for a link that exists between two neighbors.

3) C_{ij}: C_{ij} is a derivative parameter. It is derived once the L_{ij} scores of the wireless links in the considered vicinity are received. To calculate C_{ij}, the link reliabilities (the L_{ij} score) of two neighboring nodes are taken, and then the unique links reliabilities are omitted. The L_{ij} of the link between immediate source and destination (neighbors) is also not considered to calculate this parameter score, then divided by all the link reliabilities of two nodes except the L_{ij} of the link between source and destination since it is supposed to be a ratio. The following mathematical relationship sums it up.

$$C_{ij} = \frac{\sum_{i=0}^{n} L_{in} \sum_{j=0}^{n} L_{jn}}{\sum_{i=0}^{m} L_{im} \sum_{j=0}^{m} L_{jm}} \tag{4}$$

where n includes all common neighbors while m contains all the neighbors of those two nodes.

Algorithm 1: Q_{ij} Routing

Input: L_{ij} of all neighboring nodes, possible sets of node i with neighbor j

Output: Q_{ij} scores and probability of selecting next node for a given destination

Initialization:

For every destination y in N: $Q_i(j) = Q(i, j)$; For each neighbor w:

$Q_{w(j)} =?$; For all destinations j in N share neighbour information regarding link reliability's, i.e respective L_{ij} scores.; For each neighbor w, send distance vector $Q_{i-w} = [Q_i(j) : j \in N]$ to w.

Loop:

wait: (until i sees a link cost change to some neighbor w or i receives a distance vector from some neighbor w)

For each y in N:

$$D_{(ij)} = c\frac{t_t - t_p}{2}$$

$$L_{(ij)} = \frac{R_{pkt}}{T_{pkt}}$$

$$C_{ij} = \frac{\sum_{i=0}^{n} L_{in} \sum_{j=0}^{n} L_{jn}}{\sum_{i=0}^{m} L_{im} \sum_{j=0}^{m} L_{jm}}$$

$$U_{ij} = \sum_{i=0}^{n} L_{in} + \sum_{i=0}^{n} L_{jn}$$

$$Q_x(v) = min_x\left(\frac{D_{ij}}{L_{ij}U_{ij}(1 - C_{ij})}\right)$$

$$Q_x(y) = min_x(Q(x, v) + Q_v(y))$$

$$p_{ij} = \frac{Q_{i-j} + Q_{j-destination}}{1 - \sum_{k=0}^{n}(Q_{i_k} + Q_{k-destination})}$$

If Q_{ij} changed for any destination j

send distance vector $Q_i = [C_{(ij)} : jinN]$ to all neighbour

Forever

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4) U_{ij}: Compared to C_{ij} that quantifies the collective probability of shared nodes in a ratio to all other connected nodes, U_{ij} does the opposite. It tells us the collective probabilities

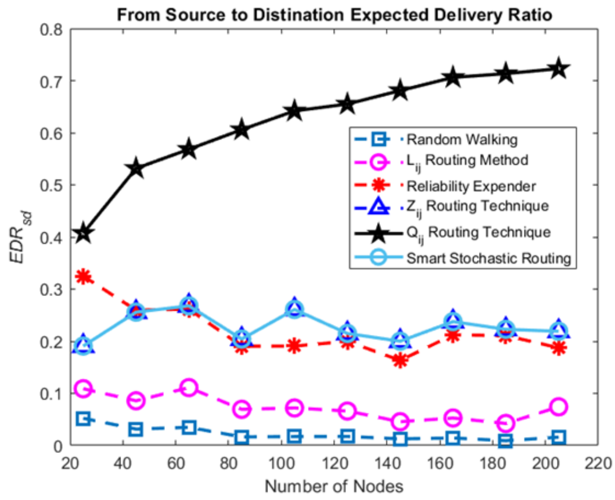

Fig. 2. Source to destination expected delivery ratio

of all the distinct nodes for any two devices. As usual, the link reliabilities of source and destination devices with other connected devices are considered. The following mathematical expression summarizes the selection of distinct node neighbors and takes their collective probabilities as a sum.

$$U_{ij} = \sum_{i=0}^{n} L_{in} + \sum_{j=0}^{n} L_{jn} \tag{5}$$

All n nodes are distinct nodes of a source device, and all the m nodes are distinct nodes of the destination device.

C. Q_{ij} Score

The Q_{ij} score quantifies the health of a link in the network. This score should be minimum for the candidate for the next hop in order to maximize the delivery ratio and minimize the delivery delay for end-to-end transmission. The Q_{ij} is defined as follows.

$$Q_{ij} = \frac{D_{ij}}{L_{ij}.U_{ij}.(1 - C_{ij})} \tag{6}$$

This mathematical relationship takes the inter-node distance D_{ij} and penalizes it with the probability of packet reception ratio at the destination.

1) A lower L_{ij} value increases the Q_{ij} score since it is a fraction. A higher L_{ij} shows that chances are higher that a packet will be transferred successfully.
2) Similarly, the sum of unique link reliabilities awards the Q_{ij} by increasing it if the U_{ij} value is high. U_{ij} may or may not be a fraction. Therefore, a higher value is desirable. A higher value guarantees that the packet will most probably be thrown out of one's neighborhood which is a desirable behavior. It is desirable for the protocol to throw a packet out of its vicinity to a rather reliable one and keep on doing it until the packet reaches its destination
3) Since C_{ij} is also a fraction, and it should contribute negatively to the Q_{ij} score, this probability is subtracted from 1. Being a fraction, a higher C_{ij} value penalizes the Q_{ij} score. The goal is to reduce the probability that a packet will be sent in the same neighborhood. It is because in dense neighborhoods, connections are strong and if the reliable connections are chosen repetitively, there is a chance that the packet will keep routing among the same set of nodes.

D. Q_{ij} Routing Algorithm

The routing algorithm that Q_{ij} employes is the traditional distance vector algorithm [18], which has been used traditionally in distributed routing in a multi-hop manner. The Q_{ij} routing algorithm, which builds on top of that Distance Vector Algorithm by redefining the cost of a communication link is defined in Algorithm 1. It can be seen here that the redefined cost of a communication link now takes into account the link reliability of the wireless link. The content of probability in determining the chances of selecting the link comes from this very quantitative factor.

IV. RESULTS AND ANALYSIS

For simulation purpose a small network is modeled as a collection of nodes represented by [x,y] coordinates drawn from a random Gaussian distribution. A square matrix of connectivity is then constructed to find the neighboring nodes based on threshold on internode distance. Those nodes falling in neighborhood are assigned a random link reliability drawn from random distribution. Derivative factors are calculated to compute the Q_{ij} score and routing is performed in between two farthermost nodes. The simulation tool used in this case is MATLAB R2020a.

A. Performance Matrices

There are a number of performance measures of routing in a distributed Internet of Things. The particular one of interest here are end-to-end delivery ratio and end-to-end delivery delay, which are very representative of initial objective of this routing mechanism.

$$ratio_{delivery} = \prod_{i=0,j=1}^{i=n-1,j=n} p_{ij} L_{ij} \tag{7}$$

where $j = i + 1$, until j is the destination node i.e., $j = n$, while $i = 0$ is the source device and j=1 is the first hop node, thus, making the delivery ratio of the first ever selected link for transmission. Since the chances of being selected are maximized for an unreliable wireless link if the $Q_{source-destination}$ is minimum among all available intermediate nodes, the probability of being selected would be

$$p_{ij} = \frac{Q_{i-j} + Q_{j-destination}}{1 - \sum_{k=0}^{n}(Q_{i_k} + Q_{k-destination})} \tag{8}$$

Here, $i - j$ presents the selected link for forwarding the packet, and probability would be evaluated based on that, while n represents all the connected devices that could act as a potential candidate for next hop, and i-k is the link

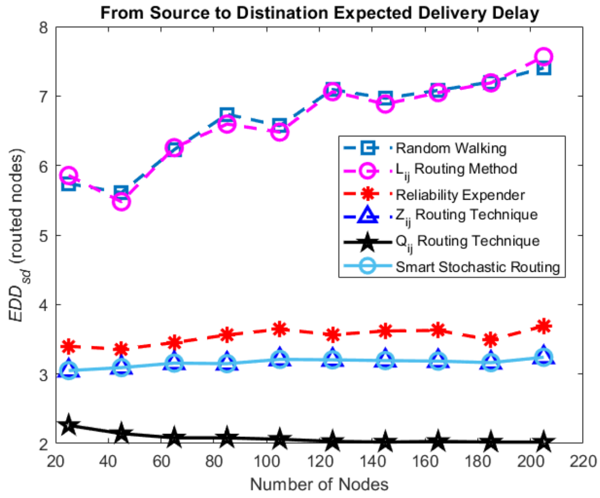

Fig. 3. Source to destination expected delivery delay

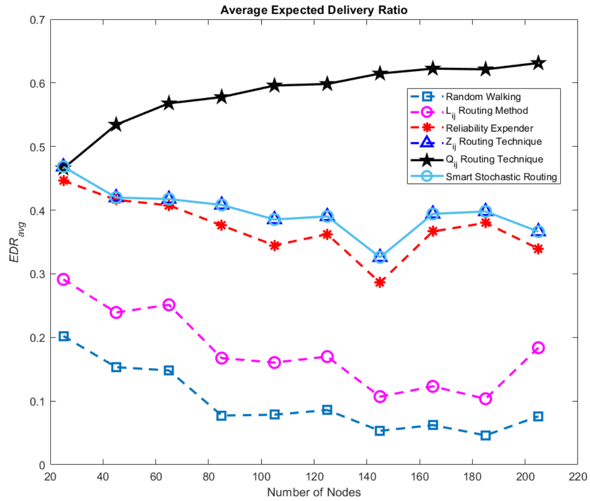

Fig. 4. Average expected delivery ratio

between them. The calculation of probability is very symbolic in nature, though not incorrect. Since the decisions taken are based on a numerical score evaluated, and it will always be link with smallest score that gets selected. Calculation of probability from the selected link among the pool of all others is, therefore, for evaluation purposes. The most important thing to notice from this relationship is that the probability for a link to be selected depends upon the ultimate destination, and, therefore, could be different for each link between i-j based upon the destination node.

The end-to-end delivery delay can be easily calculated by measuring the number of nodes encountered before reaching final destination. It is obtained by taking the length of path – 1, or the number of links jumped throughout the route, i.e.,

$$delay_{delivery} = (\sum_{i=0,j=1}^{i=n-1,j=n} Linkjumped_{ij}) - 1 \quad (9)$$

Here, $Linkjumped_{ij} = 1$ if there is a successful hop between transient devices. However, just one simulation does not demonstrate the superiority of this routing scheme. Therefore, 100 different iterations of simulation are run with 100 different networks, i.e., networks with randomly created nodes' locations/coordinates and different reliabilities (drawn from random distribution in between 1 and 0). In each iteration of a simulation, source and destination are set to be the farthest apart devices representing a wireless sensor network device that must route a packet through a distributed network in a multi-hop manner. After a path is found, end-to-end delivery ratio and end-to-end delivery delay are observed and averaged for total 'x' number of iterations the simulation ran for. End-to-end delivery ratio and delay are important measures for evaluation purposes [19]. However, there is another measure that tells how well the routing scheme works for all the other randomly placed devices with random link reliabilities. These are average delivery ratio and average delivery delay. It is done by setting each node as a source one by one and performing the routing work iteratively for 'n' number of devices in the network. For these two measures, 100 simulations are also run to get an expected value against the set of parameters. Last but not the least, it is important to study what behavior does the routing scheme demonstrate for increasing number of devices. It is important to study what happens when the number of devices increases in the network. For this purpose, simulations are run with increasing number of devices. For comparison with [7], [8], [15] [16] [17], the number of devices chosen are 25, 45, 65, 85, 105, 125, 145, 165, 185, and 205 in order to compare their performance with growing number of devices in the network. The following subsections include discussion of performance of routing scheme in four different parameters categorized according to two classification of delivery ratio and delivery delay i.e., average and source-destination.

B. Expected Delivery Ratio (Source-to-Destination)

The graph shown in Fig. 2 explains how much packets on average reach the destination for any given number of nodes in the network. It can be observed that the trend is encouraging for increasing number of nodes. The more nodes are present in the network, the better would be the expected delivery ratio. However, the growing trend slows down as more nodes are included. This is showing a trend of saturation after a certain number of devices.

C. Expected Delivery Delay (Source-to-Destination)

Expected delivery delay is the measure of an expected value of average performance in terms of how many nodes are expected to be encountered while traversing across the network. The proposed routing scheme demonstrates the best results as shown in Fig. 3. However, since the environment was modeled with random variables, the trend does not communicate progress as the number of devices increase. It is because

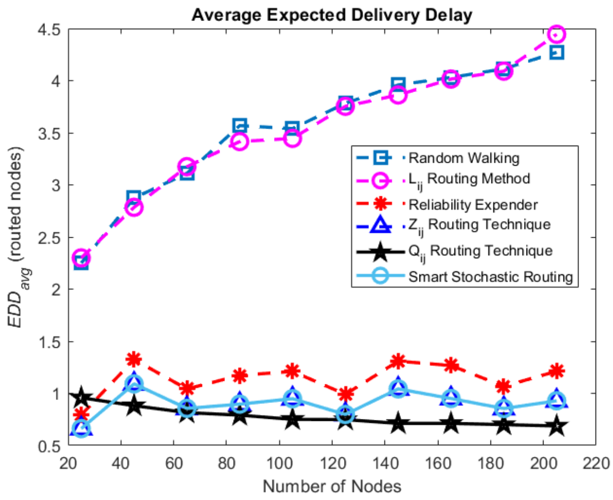

Fig. 5. Average expected delivery delay

it quickly finds out the best path in least number of devices available as well. What can easily be inferred from this graph in Fig. 3 is that the routing scheme will eventually find the best path available.

D. Expected Delivery Ratio (Average)

The average expected delivery ratio is a measure of delivery ratio taken as an average of routing performance of all the devices included in the network. Several simulations are performed to route a message from all nodes to a set destination and averaging over sampled population yields EDR_{avg}. This is an important measure of routing behavior, since it tells us how well the protocol works for the rest of the network. It is noticeable from Fig. 4 that the worst performing scenario of Q_{ij} is same as the best performing scenario from the rest of the protocols used for comparison.

E. Expected Delivery Delay (Average)

The source is updated each time the simulation ends. The performance parameters are accumulated. When all nodes set as source node are considered, the accumulated values are normalized to get an average. The desired behavior of EDD_{avg} is to have the least amount of delay regardless of the number of devices. However, the trend in Fig. 5 shows that in the longer run, the Q_{ij} performs much better than the rest of protocols with which performance is compared.

V. CONCLUSION

Routing in the Internet of Things poses numerous challenges in different scenarios. Addressing the critical challenge of delivery ratio, and latency make the routing job difficult. Distributed routing schemes are vulnerable to frequent downtime and face reliability issues. Keeping in mind these challenges, a novel stochastic routing scheme is proposed in this paper, in which link reliabilities are utilized. Stochastic routing has proven to be adaptive in such circumstances. The proposed routing scheme, called Q_{ij}, has demonstrated better results as compared to eminent stochastic routing schemes. It has been shown that there are both major differences in approach to evaluate the selection of the next hop. The benchmark schemes follow a path while taking a rather greedy approach. Contrarily, the proposed scheme considers all possible paths for evaluating the health of whole link. Though the algorithm works really good but improvements can be made in areas where it is limited by its dependence on continuous updates of distance vectors and $O(n^3)$ algorithmic complexity.

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