

# Effective Implementation of Energy Aware Polarization Diversity for IoT Networks Using Eigenvector Centrality



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**Abstract** The Internet of Things (IoT) is one the most promising area of applications for complex networks since we know that both the efficiency and fidelity of information transmission rely critically on our understanding of network structure. While antenna diversity schemes improve reliability and capacity for point-to-point links of an IoT network that employs multi-polarized antennas, it is currently unclear how implementation should depend on the network structure of the IoT and what impact structure-dependent implementations will have on the energy consumption of IoT devices. We propose an antenna diversity scheme that leverages local network structure and a distributed calculation of centrality to reduce power consumption by 13% when compared to standard selection diversity technique. The proposed approach exploits distributed eigenvector centrality to identify the most influential nodes based on data flow and then limits their antenna switching frequency proportionally to their centrality. Our results also demonstrate that by taking routers' centrality metric into account, a network can reduce antenna switching frequency by 17% while ensuring approximately 99% packet delivery rate. More broadly, this study highlights how network science can contribute to the development of efficient IoT devices.

## 1 Introduction

The Internet of Things (IoT) interconnects heterogeneous entities like sensors, actuators, wearable items and phones to develop an integrated system where these multipurpose devices can monitor their surrounding environment, react to a certain event, collect sensory data and forward the data in multi-hop fashion to back-end systems for further processing [1]. The applications of IoT span from small scale implementation such as patient monitoring, smart homes, to large scale

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© Springer Nature Switzerland AG 2020  
N. Masuda et al. (eds.), *Proceedings of NetSci-X 2020: Sixth International Winter School and Conference on Network Science*, Springer Proceedings in Complexity,  
[https://doi.org/10.1007/978-3-030-38965-9\\_17](https://doi.org/10.1007/978-3-030-38965-9_17)

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implementations of industrial monitoring, smart farming, smart cities, etc. [2, 3]. In many of these potential applications, IoT devices are deployed in environments which are not ideal for wireless communication. Environments such as industrial facilities are particularly harsh where reflection, diffraction and scattering from metal structures cause distortion to the radio signal, known as multipath fading [4]. Signal attenuation, phase shifting and inter-symbol interference caused by multipath fading significantly degrade reliability and throughput of the network.

Multi-polarized antennas are an effective solution to overcome multipath effects as they allow the receiver to have multiple copies of the transmitted signal by using orthogonally polarized antenna elements [5]. However, the problem is then to choose which antenna polarization should be used given local conditions, including network structure. Selection diversity is the simplest diversity technique used in conjunction with multi-element antennas in which the antenna polarization having the highest signal strength is chosen for transmission or reception. Due to cost constraints and limited processing capabilities of IoT devices, selection diversity uses a single radio-frequency (RF) chain and switches between polarizations to determine the 'best' polarization using a RF switch. Existing works in the literature related to selection diversity schemes primarily focus on ensuring link reliability, minimizing low bit error rate (BER) and attaining high signal-to-noise (SNR) ratio. For example, the authors of Ref. [6] developed an algorithm with quartic complexity to select optimal subset of antennas that ensures maximum SNR for systems with many transmit antennas. In Ref. [7], a low-complexity generalized selection combining (GSC) scheme is introduced, which is able to match the performance of a full diversity system in terms of outage probability and symbol error rate while utilizing only a subset of the available antennas to transmit and receive. In Ref. [8], capacity maximizing suboptimal antenna selection algorithm for medium to high SNRs is proposed to determine the transmit antenna in a Rayleigh fading environment. However, all the mentioned works required either multiple RF chains to be active simultaneously or the device to solve complex optimization problems, which is not suitable for low-cost, constrained IoT devices. Moreover, the network structures of IoT systems are often complex and hierarchical, suggesting that diversity technique might be an interesting avenue of research.

In multi-hop communication based routing, router nodes that are near the base station relay the data collected by the sensor nodes that are further away from the base. Thus, in this network, the closer a router is to the base, the higher its data traffic load will be, resulting in frequent use of selection diversity to select antenna polarization. This will cause faster depletion of energy of the routers with high data traffic compared to the routers with less traffic, i.e., far away routers. Intuitively, in an IoT network operating in multipath environment, the time between consecutive data transmission by a sensor node can be large compared to the coherence time (time over which the channel changes significantly) of the channel and thus, each transmission sees independent fading. On the contrary, as routers manage packets from multiple sensor nodes, the coherence time for routers is large relative to the time between consecutive transmission/reception which implies that the fading seen by packets are correlated. For example, IoT networks aimed at wildfire detection,

forest environment and agriculture monitoring require geographically dispersed sensor nodes to transmit sensed information periodically at a low data rate. The base station can provide valuable forecast, improve safety and efficiency by integrating the sensed data that is relayed through routers [9, 10]. This motivates us to consider controlling the use selection diversity according to nodes' data traffic load as approximated by their position in the network structure. Indeed, an IoT network can be effectively represented as a complex network [11], a graph object whose vertices correspond to sensor or router nodes while edges stand for data transmission between nodes. More specifically, we consider the problem of finding routers with high data traffic in an IoT network as a problem of finding the crucial nodes in a complex network. Then, we can leverage centrality metrics [12], which rank the nodes of a network based on their importance in a network, to identify highly congested routers. Our focus in this paper is to apply ideas from complex network science in order to implement a device-specific diversity scheme that considers nonuniform depletion of energy of routers in an IoT network.

By combining complex network theory and the concept of antenna diversity, we propose a network-wide diversity technique, where devices will use selection diversity in a periodic manner instead of using it before every transmission or reception and the period will be proportional to their centrality. In summary, the main contributions of this paper are as follows.

1. We employ the concept of eigenvector centrality to determine crucial nodes in an IoT network consisting of a large number of stationary nodes from the view point of data packet transmission and reception. The centrality is calculated by autonomous sensor and router nodes in a distributed manner which reduces computation complexity and ensures low-memory usage for low-resource, energy-constrained IoT devices compared to centralized computation.
2. In contrast to the conventional selection diversity technique that allows all devices to switch antenna element before every transmission or reception, our proposed energy-aware diversity scheme controls the switching of devices such that low-scoring routers are allowed to switch antenna more frequently compared to the high-scoring ones and hence, reduces excessive switching and is able to minimize antenna switching by at least 17%.
3. We demonstrate through simulation that the reduction of excessive antenna switching achieved by our Distributed Eigenvector Centrality (DEC) diversity approach decreases energy consumption of routers by at least 13% compared to simple network-wide selection diversity approach, without degrading network reliability.

The paper is organized as follows: Sect. 2 reviews related works. In Sect. 3, we give an overview of the type of target IoT networks and deployment environment considered. Section 4 introduces a distributed calculation of eigenvector centrality and proposes an implementation for IoT network in which an individual antenna switching rate is controlled based on its centrality in the network structure. Section 5 describes the comparison between our proposed centrality based diversity scheme and simple selection diversity scheme and Sect. 6 concludes the paper.

## 2 Related Works

A network consists of a set of nodes connected by edges which can be directed or undirected, weighted or unweighted. Centrality is often used in complex network systems to identify the relative influence of a node or edge with respect to the entire network. Various centrality measures such as betweenness, closeness and eigenvector centrality have been studied in the literature based on application context and different characteristics of a network. Betweenness centrality determines the amount of influence a node has over the information flow of a network. It first calculates the shortest path between every pair of nodes in a network and assigns a centrality to nodes based on how frequently they lie along shortest paths [13]. Closeness centrality is defined as the inverse of the average distance between a given node and all other nodes in the network [14] such that high closeness centrality indicates central nodes that have shorter distances to other nodes. However, most centrality measures are calculated based on global topology information which is prohibitive for memory-constrained, low-cost devices of an IoT network with a large number of nodes. Another popular measure is eigenvector centrality, which calculates a node's importance in a network by summing the importance of its neighbors [12]. Eigenvector centrality is defined based on the eigenvector of the network adjacency matrix such that the centrality  $\mathbf{x}$  satisfies  $A\mathbf{x} = \lambda\mathbf{x}$  where  $A$  is the  $N \times N$  adjacency matrix,  $\mathbf{x}$  is the eigenvector associated to the greatest eigenvalue  $\lambda$  of  $A$  and  $N$  is the number of nodes.

Although a node which is central by one centrality measure may be central by other centrality measures, this is not necessarily always true. Compared to betweenness centrality (measures the number of paths that pass through each node) and closeness centrality (based on average distances), eigenvector centrality is based on the idea that a central node is connected to other central nodes, which is a natural definition for centrality in an IoT network. However, one of the major disadvantage of eigenvector centrality measure is that the calculation is quite complex and complexity grows as  $N$  increases which is challenging for battery-powered nodes with limited storage and processing capabilities. In this present work, we utilize the concept of eigenvector centrality and leverage the tree structure of our IoT networks for a distributed computation of centrality, where a node relies on its next hop neighbors only to compute its individual centrality. Restricting the topology means nodes do not have to obtain information about far-away nodes which reduces resource usage.

Recently, several studies have focused on exploiting eigenvector centrality in a distributed way. For example, Ref. [15] presented a reception-equal rate allocation strategy for cooperative streaming so that all nodes receive the stream with the minimal global use of resources by using a distributed version of the eigenvector centrality. Although the proposed centrality measure can be computed distributedly, every node still needs to be aware of the full network topology to calculate the centrality. In Ref. [16], the authors studied a distributed computation of the PageRank algorithm, a variant of the eigenvector centrality. In our work, we focus

on a distributed version of the classic eigenvector centrality, which can be measured individually by each node of a directed loop-free wireless network consisted of resource constrained devices.

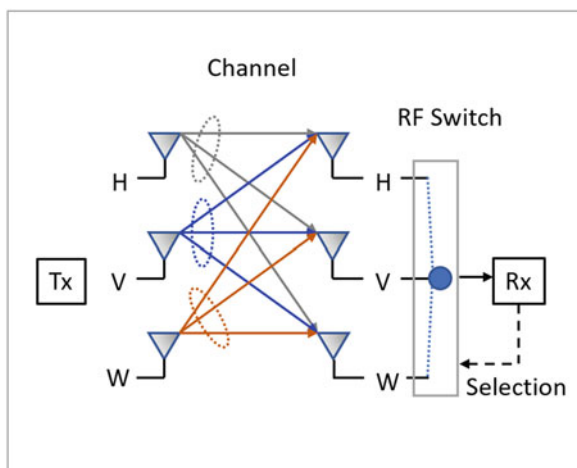
### 3 System Model

Due to scalability, low cost and ease of deployment, IoT networks are gaining increasing interests in the research community. Depending on the particular application, different network architecture may be of interest. We consider an IoT network, where both nodes and routers are autonomous and characterized as energy-constrained devices with limited memory and poor processing capabilities. Routers function as data aggregators and relay the received data to the base station, which has unlimited power supply and is far from the sensing area, in a directed multi-hop fashion through other routers. In addition, all the deployed devices are only aware of their next hop neighbors and have no global knowledge of network. An example of such network is a time-driven IoT network, used to collect spatio-temporal readings of various environmental parameters through densely deployed sensor nodes.

We assume that all devices are equipped with tripolar antenna consisting of three orthogonal mutual collocated antenna elements to create vertical (V) polarization, horizontal (H) polarization and a third polarization (W) which is perpendicular to the other two [16].

Figure 1 demonstrates available channel gains for such systems which can be described using a  $3 \times 3$  complex channel matrix. During transmission, we assume that the signal gets affected by Rayleigh fading, which is independent and identically distributed on each antenna element. Both nodes and routers use selection diversity to determine the best polarization for transmission and reception.

**Fig. 1** Block diagram of transmission and reception using tripolar antenna



To reduce hardware complexity, a single RF chain is used by the tripolar antenna which changes antenna element using a RF switch. IoT devices receive pilot symbols using different polarization from their next hop router to estimate the channel gain of all three antenna elements by means of received signal strength. The receiver antenna then selects one of the polarizations based on its estimates. The base is assumed to be unaffected by multipath fading and uses vertical polarization only for transmission.

## 4 Distributed Eigenvector Centrality

Classic eigenvector centrality, which measures how well connected a node is to other well-connected nodes in the network, is computed globally. To facilitate faster computation and reduce memory usage of resource-constrained IoT devices, we use distributed eigenvector centrality (DEC), where each device (sensor or router) will calculate their own centrality. To model the IoT network, we let  $G(V, E)$  be a directed graph with  $N$  sensor nodes and  $R$  router nodes, where  $V$  is a set of vertices representing all devices of the network and  $E$  is a set of edges representing links between the devices. To calculate the centrality of node  $k$  with neighbor set  $\{1, 2, \dots, j\}$ , we define an edge-weight matrix  $\mathbf{W}$ , which is a  $j \times 1$  column matrix, and neighbor-centrality matrix  $\bar{\mathbf{C}}_{v_k}$ , which is a  $1 \times j$  row matrix, as,

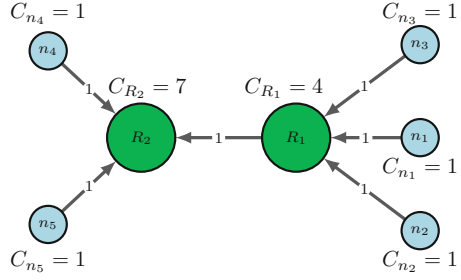
$$\mathbf{W} = \begin{bmatrix} w_{1,k} \\ w_{2,k} \\ \vdots \\ w_{j,k} \end{bmatrix}_{j \times 1} \quad \text{and} \quad \bar{\mathbf{C}}_{v_k} = [c_{v_1} \quad c_{v_2} \quad \dots \quad c_{v_j}]_{1 \times j} \quad (1)$$

here weight of each edge  $w_{i,k}$  is either 1 or 0 and  $i$  is one hop neighbor of node  $k$ . In the context of our network, a directed edge from node  $i$  to node  $k$  indicates data packet flow direction from  $i$  to  $k$ . If there is an edge from node  $i$  to node  $k$ , then  $w_{i,k} = 1$ , otherwise  $w_{i,k} = 0$ . Also,  $c_{v_i}$  denotes the centrality of the node  $i$ . The proposed centrality scheme is initialized by awarding one centrality point to each vertices. After that each node calculates its own centrality by summing the centrality of its neighbor nodes that have edges directed towards them. Thus, DEC for node  $k$  is defined as the weighted sum of the centralities of all its neighbor sensor nodes and routers and can be written as

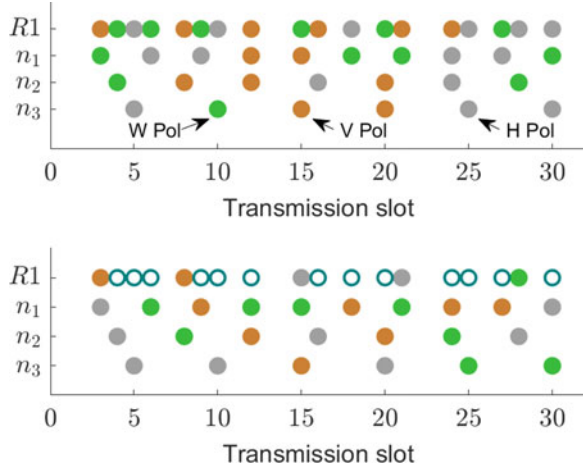
$$c_{v_k} = 1 + \mathbf{W}\bar{\mathbf{C}}_{v_k} = 1 + \sum_{i=1, i \neq k}^j w_{i,k} c_{v_i} \quad (2)$$

Figure 2 illustrates an example of centrality calculation using two routers and five sensors. Sensor nodes  $n_1, n_2$  and  $n_3$  do not have any directed edge towards them and hence each sensor has centrality 1. On the other hand,  $R_1$  has a centrality of 4 since

**Fig. 2** Sample network of two routers and five sensor nodes with routers depicted in green and sensors depicted in light blue color



**Fig. 3** An illustration of data transmission by sensors and router. Solid circles indicate usage of selection diversity before transmission while empty circles indicate no antenna switching occurred and colors represent different polarizations. *Top*: Router R1 uses conventional selection diversity *Bottom*: R1 uses centrality based selection diversity



there are three directed links from three neighbor nodes each having a centrality of 1. Although  $R_2$  is a neighbor of  $R_1$ , it does not contribute to the centrality of  $R_1$  as there is no directed edge from  $R_2$  to  $R_1$ . Similarly  $R_2$  has a centrality of 7 since it has directed edges from neighbors with centrality 1, 1 and 4.

Under the assumption that each device knows their type and total number of devices present in the network, it can compute their centrality by only using local interactions with its neighbor. Our goal is to allow nodes to limit their antenna switching based on their centrality. We can then define the interval slot for node  $k$  as

$$\lfloor s_k \rfloor = \frac{1}{(N + R)} \alpha c_{v_k} \tag{3}$$

where,  $N$  and  $R$  are the total number of sensors and routers, respectively. Also,  $s_k$  is the number of transmissions during which a node will not use selection diversity unless the signal strength of the currently used antenna branch falls below the threshold and  $\alpha$  is an integer that denotes the interval parameter. We note that the interval slot, i.e., the waiting period between two consecutive antenna switching is proportional to a node’s centrality and it increases for large values of  $\alpha$ .

Figure 3 presents an illustration of transmission rates between nodes and a router for the example network presented in Fig. 2, where sensor nodes (denoted as  $n_1, n_2,$

and  $n_3$ ) are transmitting data packets to the router  $R_1$  at different rates. We note that, when  $R_1$  uses conventional selection diversity (see Fig. 3 *Top*), it requires antenna switching before every transmission. On the other hand, when  $R_1$  employs centrality based switching (see Fig. 3 *Bottom*), antenna checks for best polarization among the three elements only after some fixed (3 in this example) transmission slots. For high centrality routers, the interval between consecutive receptions and transmissions will be smaller and hence it's highly likely that the channel conditions will not change between consecutive transmissions. Thus, restricting the use of selection diversity for such routers before every transmission will reduce excessive switching and minimize energy consumption at the same time. With a time complexity scaling linearly with the number of vertices in the network, DEC offers fast computation and requires little memory usage. Moreover, with DEC, any changes in network topology can be dealt locally as only a part of nodes need to recalculate their centrality.

#### ***4.1 Centrality Based Diversity Scheme***

We now describe the infrastructure of the IoT network that is used for simulation and also how experimental data is incorporated to assess the performance of the proposed scheme in a Rayleigh-fading environment. The network is initialized with random sensor node deployment and the base is located at one corner of the monitoring area. The routers are equidistant from one another and when a router joins the network, it sends a multicast packet to discover its adjacent sensors and routers and creates a routing table based on the received response. The time difference between two consecutive data packet transmission by sensor nodes is varied randomly between 1–10 s. Centrality is calculated in a bottom-up approach, where each sensor and router use their own routing table to calculate their centrality and share the score to their next level router only. Once calculated, devices will keep using the centrality unless there are changes in their neighborhood. If a new sensor or router joins, then their neighboring devices update centrality. After computing centrality, devices determine their individual switching rate, which defines how often a device will use selection diversity to select the best antenna element. Once a device selects a polarization for transmission/reception, it may need to wait for a couple of transmission slots to use selection diversity again and, importantly, this waiting period is chosen proportionally to its centrality. During the interval, the antenna will keep monitoring the signal strength of the currently used antenna branch and if the branch falls below a predetermined threshold, it will use selection diversity to select the best branch among the three branches. To assess the performance under a setting similar to real world environment, we exploit the signal strength and energy consumption data obtained experimentally, as described in Ref. [16], using embedded devices equipped with tripolar antennas in a high multipath environment.



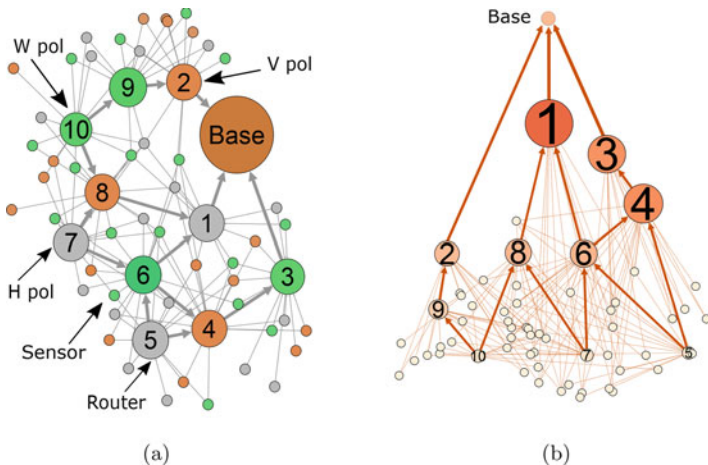
## 5 Performance Evaluation

In this section, we describe the simulation parameters used to evaluate the performance of the proposed diversity scheme. Furthermore, we also compare the results with existing selection diversity technique.

### 5.1 Simulation Model

We present the results for a case with 50 sensors and 10 routers as depicted in Fig. 4a, where devices are using different antenna polarization at a certain time. We note that, routers that are closer to the base station see substantially more data traffic compared to the routers that are far away from the base or on the edge of the sensing area. Figure 4b demonstrates the use of DEC, where high centrality is assigned to the routers that are closer to the base and tend to aggregate more data packets compared to routers that are far from the base.

In order to evaluate the performance of the proposed centrality based diversity scheme, we consider an IoT network that performs periodic data collection through sensor nodes based on IEEE 802.15.4 protocol. Sensor nodes are static and unable to relay data from other nodes. Routers receive data from other nodes and forward the data to the next hop routers in a tree-based routing fashion. We built a discrete event simulator based on Matlab where a rectangle region is used to deploy the nodes. The default parameters used in our simulation are presented in Table 1.



**Fig. 4** (a) Basic architecture of an IoT network consisting of 50 sensors and 10 routers. Colors represents different polarizations, sizes represents different type of IoT devices. (b) Representation of the network presented in (a) using DEC. Color coding and size indicates centrality of sensor and router nodes. Less central nodes have smaller size and lighter color compared to more central nodes which have larger size and darker colors

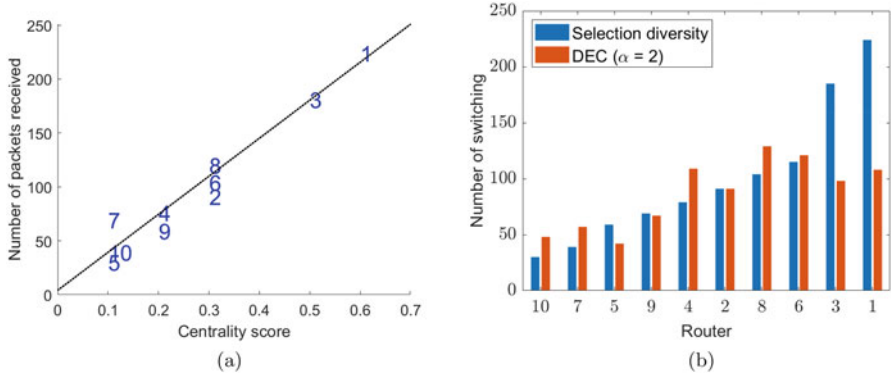
**Table 1** Simulation parameters

Parameter	Value
Area of deployment	$300 \times 300 \text{ m}^2$
Number of sensors	50
Number of routers	10
Energy: transmission	0.01 J
Energy: reception	0.008 J
Energy: switching	0.001 J
Energy: pilot packets (transmission/reception)	0.002 J
Data packet size	32 bytes
Data rate	250 kbit/s
Pilot packet size	16 bytes
Battery capacity	18.7 kJ
Frequency	2.4 GHz
MAC protocol	802.15.4
Number of repetitions	10

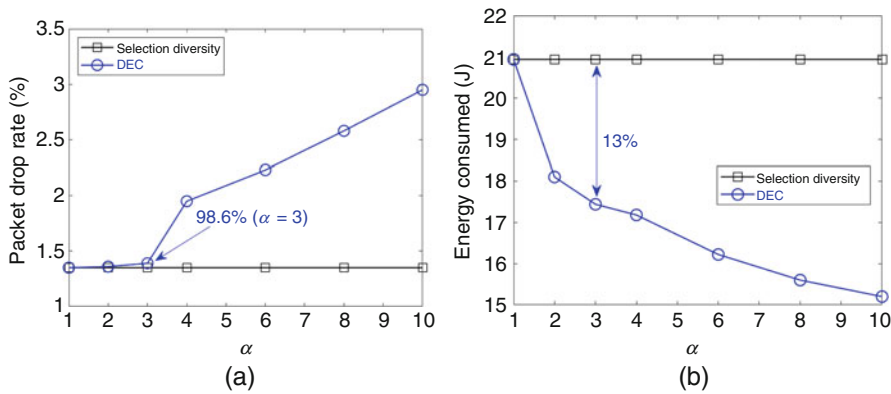
We then run a comparative analysis between our proposed scheme and selection diversity technique. Three performance metrics are used: switching frequency, packet delivery ratio and energy consumption. In the baseline scenario, we consider a network, where each device uses selection diversity to determine the best antenna element for transmission and reception. To analyse the performance of our proposed model, we experiment with different network sizes in terms of the number of sensors and routers.

## 5.2 Simulation Results

Figure 5 presents our results on the impact of the centrality metric in decreasing antenna switching rate. We focus on the routers only since sensor nodes are assumed to be unable to perform data forwarding. Figure 5a illustrates the centrality of routers calculated based on Eq. (2) and normalized by the total number of devices 60. We note that few routers stand out amongst other routers due to high centrality and thus, serve as central points of data aggregations. We also see that the high scoring routers receive and forward more data traffic, which deplete their energy rapidly, compared to other routers with low centrality values. The results also show the heterogeneity among routers in terms of data traffic through them and hence, reinforces the requirement of node-specific diversity scheme. Figure 5b shows the effect of using interval parameter  $\alpha$ , where the antenna switching of routers with high centrality are restricted compared to other routers. Even though the number of switching varies for routers for different simulation runs, we observe that when  $\alpha$  is set to 2, our proposed diversity scheme decreases antenna switching approximately by 17% compared to the conventional selection diversity.



**Fig. 5** (a) The number of packets received by routers, plotted against their normalized centrality. It can be seen that routers which receive more data packets have higher centrality. (b) Comparison between selection diversity and the proposed technique in terms of switching frequency. Routers are plotted in ascending order based on the number of switching. Note that the number of switching is decreased for high scoring routers



**Fig. 6** Comparison between selection diversity and the proposed technique for different values of  $\alpha$  in terms of (a) packet drop rate and (b) energy consumption rate, for a network consisting of 50 sensor nodes and 10 routers. As can be seen in the figure, for  $\alpha = 3$ , our proposed scheme has approximately 99% successful packet delivery rate and reduces energy consumption by 13% compared to the selection diversity technique

Figure 6 demonstrates the use of interval parameter by comparing the centrality based diversity scheme with selection diversity technique in terms of packet delivery and energy consumption for different values of  $\alpha$ . From Fig. 6a, we note that when  $2 \leq \alpha \leq 3$ , the proposed centrality based diversity scheme is on par with selection diversity technique in terms of packet delivery rate. However, as  $\alpha$  increases, packet drop rate increases for our proposed scheme compared to the selection diversity. Since a large value of  $\alpha$  increases the waiting time between consecutive antenna polarization selection, network reliability decreases. Figure 6b

demonstrates the influence of  $\alpha$  on the energy consumption of routers, where energy consumption includes power consumed due to antenna switching, transmission and reception of both pilot packets and data packets. Since a large value of  $\alpha$  implies that more routers have reduced switching rate, the energy consumption decreases considerably. However, restriction in updating antenna polarization for longer period results in greater packet loss compared to the selection diversity. Therefore, selecting an appropriate value of  $\alpha$  is crucial for achieving satisfactory performance in terms of reliability and energy efficiency.

## 6 Conclusion

In this work, we present an energy-aware polarization diversity scheme based on node centrality metric for IoT networks. We consider a typical IoT network composed of sensor devices that periodically sense data and utilizes tripolar antenna to forward it to the base station through routers in a multi-hop fashion. The proposed diversity scheme leverages distributed eigenvector centrality metric, calculated by all IoT devices individually without requiring global information about the network topology, to measure a router's importance based on the importance of its connected neighbors. The identification of most influential router nodes allows us to employ a node-specific diversity scheme that lets low scoring routers to switch polarization more frequently compared to high scoring routers and hence decreases excessive switching over the whole network.

Our results suggest that methods to rank the influence of different nodes in complex networks can be applied in IoT networks to save energy consumption without compromising fidelity. Indeed, our simulation results demonstrate that the proposed centrality based approach reduces switching by at least 17% compared to the approach of utilizing selection diversity for all sensor and router nodes irrespective of their roles. This shows that the proposed scheme is able to lessen energy consumption by at least 13% compared to the conventional selection diversity while offering similar network reliability. In future work, we plan to implement the proposed scheme in real devices using various topologies and routing strategies.

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