Applying Swarm Intelligence to a Novel Congestion Control Approach for Wireless Sensor Networks

[Invited Paper*]

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ABSTRACT
Recently, sensor networks have attracted significant research interest. However, most studies have mainly focused on protocols for applications in which network performance assurances are not considered essential. With the emergence of mission-critical applications, performance control mechanisms are considered of prime importance. Performance control can be carried out by robust congestion control approaches that aim to keep the network operational under varying network conditions. Swarm intelligence is successfully employed to combat congestion by mimicking the collective behavior of bird flocks. In this way, the emerging global behavior of minimum congestion is achieved collectively. A flock-based congestion control (Flock-CC) approach was proposed in the past. This paper presents a new, simpler Flock-CC approach. Performance evaluations focus on parameter setting and on comparative studies between the new and the earlier version of Flock-CC.

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1. INTRODUCTION
Wireless sensor networks (WSNs) [1] can be used as platforms for health monitoring, process control, environmental observation, battlefield surveillance etc., and are expected to operate unattended for extended durations. Typically WSNs comprise of small, cooperative devices (nodes) which may be constrained by computation capability, memory space, communication bandwidth and energy supply. These nodes may interact (a) with the environment so as to sense or control physical parameters, and (b) with each other in order to exchange information or forward data towards one or more dedicated sink nodes. Typically, WSNs operate under light load. However, large, sudden, and correlated-synchronized impulses of data may suddenly arise in response to a detected or constantly monitored event.

Large numbers of generated packets in conjunction with variable wireless network conditions, may result in unpredictable behavior in terms of traffic load variations and link capacity fluctuations. The problem is worsened due to topology changes driven by node failures or mobility. These stressful situations are likely to occur in WSN environments and are expected to cause congestion.

Congestion control (CC) is one of the most basic components of a performance controlled network. The resource limited and unpredictable nature of WSNs necessitates *decentralized, robust, self-adaptive*, and *scalable* congestion control/congestion avoidance mechanisms. Novel CC approaches for WSNs should be *simple* to implement at individual node level with *minimal exchange of information*. Nature-inspired (natural) designs have inherent powerful characteristics and are much more simpler than man-made designs [7]. Natural systems usually exhibit remarkable survivability and robustness to external stimuli and internal perturbations or loss of units, as well as excellent scaling properties. Adaptation is one of the major strengths of bio-systems as they must respond to addition or removal of members, as well as to sudden changes in the environment.

The proposed approach mimics the *flocking behavior of birds*, where packets are modeled as birds flying over a topological space, e.g. a sensor network. The main idea is to 'guide' packets to form flocks and flow towards a global attractor (sink), whilst trying to avoid obstacles (congested regions).

This paper aims at presenting and evaluating the new version of the Flock-CC approach, as compared to [4], [5], and [6], where an older version was described. The two versions have some important differences. Specifically, the new version mimics more faithfully the bird flocking paradigm, as presented by Couzin at al. [10]. Also the new version is simpler, with only one tunable parameter instead of three (hence easier to tune and thereafter deploy), while it maintains comparably good performance characteristics.

The rest of this paper is organized as follows. Section 2 presents existing approaches to congestion control in WSNs. Section 3 introduces the notions of swarm intelligence and the flocking behavior of birds. Section 4 deals with the new version of the Flock-CC approach. Section 5 presents performance evaluation results of the new Flock-CC approach as well as comparative results between the two versions. Section 6 draws conclusions and proposes areas of future work.

2. RELATED WORK

Early studies in the area of sensor networks had mainly focused on more fundamental networking problems, e.g. medium access control [11], topology [12], routing [2], and energy efficiency [3] largely ignoring network performance assurances. Lately, with the emergence of mission-critical applications (e.g. health monitoring), there has been an increased interest in performance control mechanisms [17].

Various conventional CC approaches can be found in WSNs literature based on traffic manipulation (e.g. rate adaptation [19], multi-path routing [15]), topology control (e.g. clustering formation [13]), and network resource management (e.g. power control, multiple radio interfaces [20]). However, some of these CC schemes are based on traditional methodologies known from the Internet, as for example, the additive increase multiplicative decrease (AIMD) rate control [19], [15]. This model is not very effective in WSNs because it has high overhead, and also results in a saw-tooth rate behavior [16] which may violate the QoS requirements.

It is worth pointing out that there is no nature-inspired study that has explicitly focused on CC for WSNs. Instead, there are quite a few SI-based studies for sensor and adhoc networks that propose congestion control policies as part of protocols dealing with other issues, as for example routing. A notable related approach is (AntSensNet) [9], an ant-based multi-QoS routing protocol for sensor networks that uses clustering to avoid congestion. Another well known approach is AntHocNet [8], an ant-based algorithm for multi-path reactive and proactive routing in mobile ad hoc networks, which incorporates congestion awareness in an end-to-end manner. Both approaches are based on ideas from Ant Colony Optimization. Both AntHocNet and AntSenseNet are quite complicated protocols involving a large number of parameters and equations, which may hinder widescale deployment. These parameters have to be tuned for a variety of network and traffic conditions since they can be sensitive to the environment. This study proposes a simpler SI-based approach with only one parameter.

3. SWARM INTELLIGENCE

Social groups found in nature (e.g., bird flocks, etc.) carry out their tasks collectively in order to contribute to a common goal. Even though individuals coordinate to accomplish a given global mission in a complex world (e.g., migration, nest building, defence against predators, foraging, etc.), an individual has only local perception of the surrounding environment and exhibits specific behavioral tendencies which are governed by a few simple rules. WSNs in many ways, have common characteristics to social groups (e.g., nodes can be likened to constituents of these social groups) as they are in great need to accomplish their tasks collectively (by simple neighbor-to-neighbor interactions), in a decentralized manner, and in the absence of (external) central supervision.

The proposed approach involves reference to artificial bird flocks consisting of individuals with finite range of perception which interact with each other as well as with the environment. The design of the interactions in packet groups is influenced by the study of artificial flocks such as the model of Couzin et al. [10]. According to Couzin et al., the behavior of each individual is influenced by other individuals within its neighborhood. In the model of Couzin et al., each individual attempts to maintain a minimum distance from others within a 'zone of repulsion' (ZoR), modeled as a sphere, centered on the individual. If there is no neighbor within the ZoR, the bird responds to others within the 'zone of orientation' (ZoO) and the 'zone of attraction' (ZoA). The collective flocking behavior of birds is considered an emergent behavior arising from a few simple behavioral rules that are followed by each individual. These behavioral rules govern individual-level interactions which collectively result in the emergence of group-level transitions.

4. THE NOVEL FLOCK-CC APPROACH

In the Flock-CC approach, a WSN is viewed as a virtual ecosystem, where multiple packets are generated at source nodes and must be directed towards a dedicated sink node. The main idea of the proposed Flock-CC model is to *'guide' packets to form groups or flocks, and flow towards a global attractor (sink), whilst trying to avoid obstacles such as congestion regions and dead zones (regions with failing nodes)*, as illustrated in Fig. 1.

Each packet is analogous to a bird with dynamic position and direction updates, which 'flies' over the network undergoing successive hop-by-hop transitions over discrete points in the 2D space, defined by the positions of hosting nodes (this is different than Couzin's model, which is set in a continuous 3D space). The set of sensor nodes comprises the

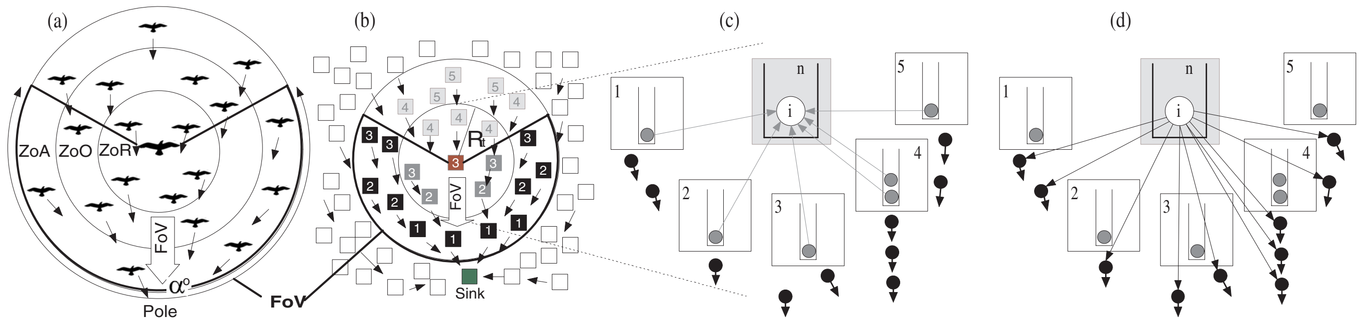

Figure 2: (a) A bird flock moving polewards under the influence of the magnetic field of the Earth (black arrows). The FoV of the bird placed in the center extends forward in the direction of the magnetic pole. (b) Packets will move sinkwards under the influence of the artificial magnetic field (black arrows). The number on each node indicates the hop distance from the sink. The field of view (FoV) of packet i extends forward in the direction of the sink. The ZoR and ZoA around packet i are redefined as circular zones, except for an area behind the packet i that is outside the FoV. (c) Repulsion forces exercised on packet i from packets in the ZoR (on heavy-gray-shaded nodes). (d) Attraction forces exercised on packet i from packets in the ZoA (moving to black-shaded nodes).

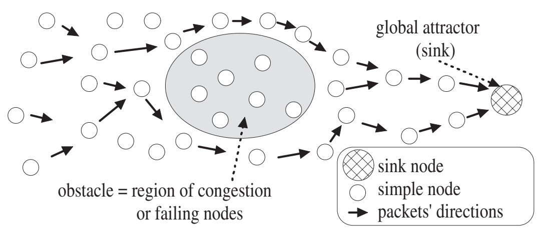

Figure 1: Packet flock moving towards sink whilst avoiding 'obstacles'.

environment where packets move. The sequence of transitions determines the packet's (bird's) trajectory from its source to the sink.

Motivated by the behavioral rules of the Couzin's model that result in moving individuals behave like a flock, *each packet is (a) repelled from neighboring packets located on nodes at close distance, (b) attracted to neighboring packets located on nodes at medium distance, (c) oriented and attracted to the global attractor (sink), and (d) experience some perturbation that may help the packets to pick a random route (i.e. trading exploration versus exploitation).*

Consider a network of N autonomous nodes, $N > 0$, that are able to generate packets. A finite queue is associated with each node, while the node's throughput is constrained by the wireless channel capacity. A packet i and its current hosting node $n \in \{1,..,N\}$ (i.e. packet i is residing in the queue of node n) are taken as points of reference in order to define and discuss repulsion and attraction zones, the magnetic field and the field of view. The position of node n determines the position of the hosted packet i.

All quantities defined herein are regularly sampled at discrete time intervals of T seconds at each sensor node. Then, the values of these quantities are broadcasted periodically (every T seconds) to all neighboring nodes (within transmission range), using a dedicated control packet. These period control packets are also used to update information about the connectivity of neighboring nodes.

Motivated by the limited visual perception of birds, packet i cannot 'see' and interact with all packets on nodes in its neighborhood. Packet i can perceive only a fraction of packets, i.e. those located in the FoV, on the observable world of the packet. In general, the orientation of a bird's FoV can be set towards any direction, driving the movement of the bird accordingly. The orientation of a bird's FoV can be affected by the presence of magnetic fields. Migratory birds that need to travel polewards turn the orientation of their head, and thus their FoV, towards the pole (global attractor) as shown in Fig. 2(a). In the same context, the sink node is seen as an artificial magnetic pole within the sensor network and packets are expected to 'fly sinkwards' under the influence of the artificial magnetic field as shown in Fig. 2(b). Therefore, the FoV of packets is influenced by the artificial magnetic field and extends forward in the direction of the sink node. The direction of the sink is determined on the basis of the hop distance parameter, $h_j(k)$, $j \in \{1,..,N\}$, indicating the number of hops between each node j and the sink at the kth sampling period.

As shown in Fig. 2(b), the ZoR is defined as a circular zone of radius R_t, except for an area behind the packet i ('blind' area). The ZoR involves packets on heavy grey-shaded nodes which are at shorter or equal hop distance compared with the current hosting node within the FoV. Practically speaking, these packets reside in the queues of the grey-shaded nodes. Therefore, packet i is repelled from these (gray-shaded) packets as illustrated in Fig. 2(c). Similarly, the ZoA is the outer circular zone of Fig. 2(b) that includes packets on black-shaded nodes. Due to the fact that the transmission range of the black-shaded nodes does not reach node n, it is not possible to obtain information at node n about the number of packets on the black-shaded nodes with one broadcast message. However, this information is locally available at node n by measuring the number of packets moving away from nodes one hop away to nodes two hops away. Therefore, packet i is attracted to these black-shaded packets as illustrated in Fig. 2(d).

The repulsive and attractive forces are synthesized by the decision making process which is invoked by the hosting node of each packet and results in selecting the most desired next hop node. The synthesis of repulsive and attractive forces is captured by a desirability function. An M-dimensional desirability vector, $\overrightarrow{D}(k)$, is used where $M \leq N$, is the number of potential new hosting nodes at the kth sampling period. Each element, $D_{nm}(k)$, of the vector $\overrightarrow{D}_n(k)$ represents the desirability for each node $m, m \in \{1, .., M\}$ measured at node n, given by:

$$D_{nm}(k) = s_{nm}^{norm}(k) - q_{nm}^{norm}(k), \tag{1}$$

where

$$s_{nm}^{norm}(k) = \begin{cases} \frac{s_{nm}(k)}{s'_{nm}(k)} & \text{if } s'_{nm}(k) > 0; \\ \xi & \text{otherwise,} \end{cases} \tag{2}$$

where $\xi \in [0, 1]$, the function $s_{nm}^{norm}(k)$ is the ratio of the successfully transmitted packets from node m to nodes two hops away from node n, $s_{nm}(k)$, divided by the total number of all packet transmission attempts (including retransmissions), $s'_{nm}(k)$, at each node m, and

$$q_{nm}^{norm}(k) = \frac{q_{nm}(k)}{Q_m}, \tag{3}$$

where the function $q_{nm}^{norm}(k)$ reflects the ratio of the number of packets in the queue of node m, $q_{nm}(k)$, divided by the queue capacity of each node m, Q_m.

An idle node m, i.e. with zero total transmission attempts ($s'_{nm}(k) = 0$) does not provide any evidence of the wireless channel quality in the vicinity of the node. Parameter ξ is introduced as the normalized attraction force exercised by each node l that was previously idle ($s'_{nl}(k) = 0$). High values of ξ result in *packet spreading* since packets are attracted to idle nodes (most probably at the borders of the flock), whereas small ξ values lead to *coherent flock motion*. A preliminary set of investigations for a good compromise value for ξ is carried out in Section 5.

After the evaluation of the desirabilities of all potential new hosting nodes, the decision making process isolates the set of nodes with shorter hop distance than the current hosting node. This selection has the highest priority. If none of these nodes is reachable, the set of nodes with equal hop distance is selected; otherwise the set of nodes with longer hop distance is selected. Then, the selected nodes are sorted in descending order by their desirability and the new hosting node is randomly selected as described below.

In the new Flock-CC approach, randomness is implemented on the basis of selection methods used in genetic algorithms, for example, roulette wheel selection or rank based selection. Due to space limitations, only rank based selection was evaluated in this study. Rank based selection ranks each individual i based on its fitness and a new fitness value f_i is assigned according to the rank the individual receives. *Individuals in Flock-CC are the potential new hosting nodes, i.e. $J = M$, and desirability is seen as the fitness of each potential new hosting node.* The probability p_i of an individual to be selected is equal to the fitness (desirability) of the individual divided by the total fitness (desirabilities) of all the individuals, as follows:

$$p_i = \frac{f_i}{\sum_{j=1}^{J} f_j}. \tag{4}$$

The new version of the Flock-CC approach involves only one tunable parameter, ξ, compared to the older version [4], [5], [6] which used three parameters, α, e and c, in the desirability function. The larger the number of tunable parameters, the more complex the issues related to fine tuning them under different network and traffic conditions.

5. PERFORMANCE EVALUATIONS

This section evaluates the performance of the new Flock-CC approach and provides a comparative study among the two Flock-CC versions through simulations conducted using the ns-2 network simulator [18].

The evaluation topology consists of 300 homogeneous nodes deployed in a lattice topology over an area of $300 \times 300\ m^2$. The evaluation scenario involved the activation of 10 nodes placed in the same neighborhood, 7 hops away from the sink. In practise, it is quite common to have nodes closely located to each other being activated almost at the same time when an external stimulus (event) is detected. In each scenario, each active node generated constant bit rate traffic at the rates of either 25, or 35, or 45 pkts/s when triggered by an event. These three cases can be considered as slightly congested, congested, and heavily congested, respectively. The buffer capacity of each node was set to 35 KB. The CSMA-based IEEE 802.11 MAC protocol with 2 Mbps transmission rate was used.

The parameter ξ was chosen to range from 0 to 1 to allow zero spreading to full spreading of the flock. The time between successive control packets, T (sampling period), was assigned the values $0.5, 1.0, 1.5$ and 2.0s.

Each scenario, using different combinations of parameter values, was executed 30 times and the mean values of the metrics over all scenarios are presented below. In selected figures, the mean values are supplemented with 95% confidence intervals[1]

5.1 Selection of parameters ξ and T

Fig. 3 illustrates the influence of parameters T and ξ on packet delivery ratio (PDR), end-to-end delay (EED) and packet loss for the traffic rate of 35 pkts/s.

At low ξ values $(0, 0.25)$, weak attraction was exercised by each idle node. Since idle nodes are usually found at the borders of the packet flock, low ξ values 'force' packet flocks to move in a coherent formation. In this case, a number of available paths were left unexploited while other (popular

[1]When dealing with non-normal distributions, 'confidence intervals' are used as a measure of variability instead of using the standard deviation. A 95% confidence interval contains the middle 95% of the numbers in a list.

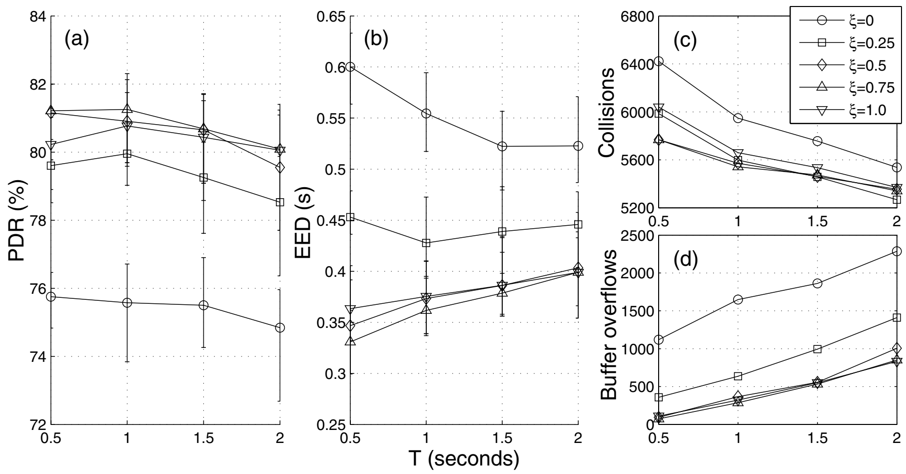

Figure 3: Packet delivery ratio (PDR), end-to-end delay (EED), and packet loss, new Flock-CC, 35pkts/s.

and perhaps, shorter paths to the sink) faced overloading, thus resulting in a high number of buffer overflows, as shown in Fig. 3(d). Increasingly, the high number of overflows led to a large number of retransmissions, and thus the increased number of collisions, as illustrated in Fig. 3(c). The high number of packet losses at low ξ values contributed to the steep decrease of PDR, while the high number of retransmissions led to the increase in EED. The effects on PDR and EED are illustrated in Figs. 3(a) and (b) respectively. On the other hand, at high ξ values (close to 1), each idle node was exercising strong attraction causing high packet spreading towards the border of the flock. Packet spreading was more intensive at $\xi = 1$, minimizing the number of buffer overflows but exhibiting a slightly higher number of collisions compared to scenarios with $\xi = 0.25 - 0.75$, especially for $T = 0.5$s. Figs. 3(a) and (b) show that the highest PDR and the lowest EED values were achieved for $\xi = 0.75$ compared to all other values of ξ. This value of ξ provides a balanced interplay between cohesion and spreading of packet flocks within the network.

An interesting observation is that the highest PDR, around 81.5%, was observed for $T = \{0.5, 1\}$s and $\xi = 0.75$, while PDR exhibited slight decrease for $T = \{1.5, 2\}$s. Similarly, the lowest EED was observed for $T = 0.5$s and $\xi = 0.75$. At low T values where control packets were broadcasted quite frequent, the Flock-CC mechanism was kept updated regarding the network state. It is worth noting that frequent updates are of prime importance in scenarios with failing nodes. This of course happens at the cost of higher energy expenditure. On the other hand, at high T values, where the desirability function was evaluated infrequently[2], packets tended to choose with high probability the same new hosting node over a longer time period leading to overloading (high queue occupancy) of the chosen node.

As can be seen in Figs. 3(c) and (d), the number of collisions dominated the number of buffer overflows for all values of T and ξ, while results revealed that the overwhelming majority of packets were lost within the hotspot area. The high number of collisions is a frequently occurring phenomenon in WSNs due to the shared wireless medium. In these environments, packets collide before reaching the receiver node and thus, buffers are less frequently filling up.

Taking the previous discussions into consideration, a good compromise value for parameters T and ξ achieving high PDR as well as low EED and low packet loss are 0.5s and 0.75 respectively. The same observations are recorded for lower (25 pkts/s) and higher (45 pkts/s) traffic rates.

5.2 Comparative evaluations

In this section, the new Flock-CC approach was compared against the older approach. Based on the results of the previous section, the sole parameter of the new Flock-CC approach, ξ, was set to 0.75, while T was set to 0.5s. In accordance with [14], in the older version of the Flock-CC

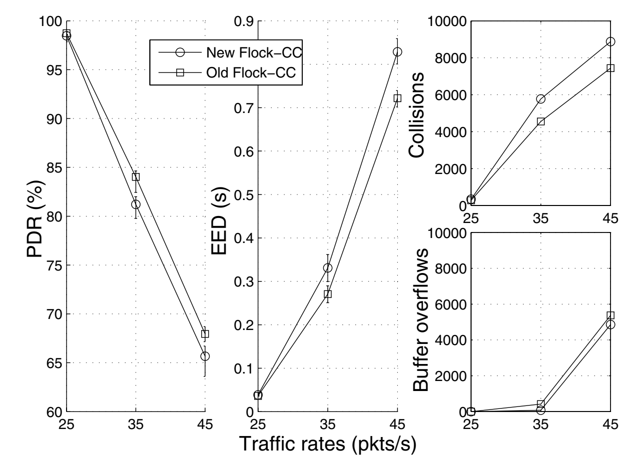

Figure 4: Comparative experiments, new Flock-CC vs. old Flock-CC for all traffic rates.

[2]Recall that the desirability function is evaluated once every sampling period and packets to be sent within this period chose the most desirable node.

approach, a good compromise combination of the design parameters values achieving high packet delivery ratio (PDR), low end-to-end delay (EED), and low energy tax in a uniform grid topology was $\alpha = 0.5, e = 0.5$ and $c = 0.25$. The sampling period T was set to 1.5s. This 'best set' of tuning parameters was found after extensive simulation evaluations, considering several representative scenarios.

Fig. 4 shows the results of the comparative evaluations in terms of PDR, EED and packet loss. It can be observed that at low traffic rates (25 pkts/s) both approaches exhibited the same performance in terms of all metrics, while at higher traffic rates (35 and 45 pkts/s) the older Flock-CC approach achieved slightly higher PDR (around 2%) and shorter EED ($0.5 - 1$s) than the new approach. The small gains stemmed primarily from the difference in the number of collisions at high traffic rates. The older Flock-CC approach managed to provide a better balance between cohesion and spreading of packet flocks within the network. However, these gains are a tradeoff versus the complexity of tuning, and its universality as tuning parameters can be sensitive to the environment.

6. CONCLUSIONS AND FUTURE WORK

The aim of this study was to design a novel nature-inspired congestion control mechanism for WSNs. This paper proposed the new version of the flock-based congestion control (Flock-CC) approach based on the synchronized group behavior of birds flocks and their ability to avoid obstacles (i.e. congestion regions) in order to control the motion of packet flocks through a network of constrained sensor nodes.

The new Flock-CC approach is more efficient in terms of implementation simplicity than the older version since the three tunable parameters of the older version, α, e and c, were substituted by only one parameter ξ. The implementation simplicity comes at the cost of a slight performance degradation in terms of PDR, EED and packet loss at high traffic rates, which is considered as an acceptable tradeoff.

The future work will provide a more thorough investigation of the influence of the tunable parameter ξ, including an attempt to better understand the behavior of the new Flock-CC approach under failing nodes. Also, extensive simulations are needed to show the self-adaptive behavior of the new Flock-CC approach under varying network and traffic conditions as well as the robustness of the proposed approach against failures. In addition, the new Flock-CC approach will be compared against other related approaches like AntHocNet and AntSensNet.

7. ACKNOWLEDGMENTS

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