Congestion Control in Autonomous Decentralized Networks based on the Lotka-Volterra Competition Model*

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Abstract. Next generation communication networks are moving towards autonomous infrastructures that are capable of working unattended under dynamically changing conditions. The new network architecture involves interactions among unsophisticated entities which may be characterized by constrained resources. From this mass of interactions collective unpredictable behavior emerges in terms of traffic load variations and link capacity fluctuations, leading to congestion. Biological processes found in nature exhibit desirable properties e.g. self-adaptability and robustness, thus providing a desirable basis for such computing environments. This study focuses on streaming applications in sensor networks and on how congestion can be prevented by regulating the rate of each traffic flow based on the Lotka-Volterra population model. Our strategy involves minimal exchange of information and computation burden and is simple to implement at the individual node. Performance evaluations reveal that our approach achieves adaptability to changing traffic loads, scalability and fairness among flows, while providing graceful performance degradation as the offered load increases.

Key words: autonomous decentralized networks, congestion control, lotka-volterra

1 Introduction

Rapid technological advances and innovations in the area of autonomous systems push the vision of Ambient Intelligence from concept to reality. Networks of autonomous sensor devices offer exciting new possibilities for achieving sensory omnipresence: small, (often) inexpensive, untethered sensor devices can observe and measure various environmental parameters, thereby allowing real-time and fine-grained monitoring of physical spaces around us. Autonomous decentralized networks (ADNs) as for example, Wireless Sensor Networks (WSNs) [1], can be used as platforms for health monitoring, battlefield surveillance, environmental observation, etc.

Typically, WSNs consist of small (and sometimes cheap), cooperative devices (nodes) which may be constrained by computation capability, memory space, communication

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bandwidth and energy supply. The uncontrolled use of the scarce network resources is able to provoke congestion. Thus, there is an increased need to design novel congestion control strategies possessing self-* properties like self-adaptability, self-organization as well as robustness and resilience, which are vital to the mission of dependable WSNs. Biological processes which are embedded in decentralized, self-organizing and adapting environments, provide a desirable basis for computing environments that need to exhibit self-* properties. In addition, their constrained nature necessitates simple to implement strategies at individual node level with minimal exchange of information.

Simple mathematical biology models [2] which aim at modeling biological processes using analytical techniques and tools are often used to study non-linear systems. Population dynamics has traditionally been the dominant branch of mathematical biology which studies how species populations change in time and space and the processes causing these changes. Information about population dynamics is important for policy making and planning and in our case is used for designing a congestion control policy. In this study, nature inspired models are employed to design a scalable and self-adaptable congestion control algorithm for streaming media in WSNs. **Based on the Lotka-Volterra (LV) competition model, a decentralized approach is proposed that regulates the rate of every flow in order to prevent congestion in WSNs**. The LV-based congestion control (LVCC) mechanism is targeted for dependable wireless multimedia WSNs [3] involving applications that require continuous stream of data.

Based on analytical evaluations performed in [4], the LVCC model guarantees that the equilibrium point of the system ensures coexistence of all flows, with stability and fairness among active flows when some conditions (presented below) are satisfied. In this paper, the validity of the analytical results is further investigated by simulating complex scenarios that cannot be formally tested. Performance evaluations are based on simulation studies conducted in Matlab and in the network simulator NS2 [5], and focus on scalability, graceful performance degradation, fairness and adaptability to changing conditions. Results have shown that the LVCC approach provides adaptation to dynamic network conditions providing scalability, fairness and graceful performance degradation when multiple active nodes are involved.

The remainder of this paper is organized as follows. Section 2 deals with the problem of congestion in ADNs and discusses previous work. Section 3 presents the analogy between ADNs and ecosystems. Section 4 proposes our bio-inspired mechanism. Section 5 evaluates the performance of our mechanism in terms of stability, scalability and fairness. Section 6 draws the conclusion and future work.

2 Congestion in AD Networks

There are mainly two types of congestion in WSNs: (a) **queue-level congestion** and (b) **channel-level congestion**. Traditionally, either high queue occupancy or queue overflow (queue drops) were considered to be key symptoms of congestion (queue-level congestion). However, simulation studies conducted by [10] and [11] revealed that in WSNs where the wireless medium is shared using Carrier Sense Multiple Access (CSMA)-like protocols, wireless channel contention losses can dominate queue drops and increase quickly with offered load. The problem of channel losses (channel-level congestion) is worsened around hot spot areas, as for example, in the area of an event, or around the sink. In the former case, congestion occurs if many nodes report the same event concurrently, while in the latter case congestion is experienced due to the converging (many-to-one) nature of packets from multiple sending nodes to a single sink node. These phenomena result in the starvation of channel capacity in the vicinity of senders, while the wireless medium capacity can reach its upper limit faster than queue occupancy [12]. Queue-level congestion is mainly attributed to the constrained nature of nodes consisting an autonomous decentralized network (e.g. limited memory and computation power), whereas channel-level congestion can be influenced by the broadcast nature of wireless networks as well as traffic variations.

Congestion causes energy waste, throughput reduction, increase in collisions and retransmissions at the medium access control (MAC) layer, increase of queueing delays and even information loss leading to the deterioration of the offered QoS and to the decrease of network lifetime. Also, under traffic load, multi-hop networks tend to penalize packets that traverse a large number of hops, leading to large degrees of unfairness.

Congestion control (CC) policies in ADNs are fundamentally different than in the traditional TCP/IP Internet, which is based on source-destination pair with reliable communication model, also involving retransmission of lost packets. This reliable end-to-end principle is tightly coupled to the client-server model of TCP/IP communication. However, this model is not very effective for ADNs, where delivery of data to a gateway (sink), without retransmission of any lost packets, is the normal objective. Their constrained and unpredictable nature provokes increased latency and high error rates that may result in reduced responsiveness e.g. for end-to-end congestion detection, leading to higher energy consumption (e.g. very high packet loss during long periods of congestion). These problems drive the need for decentralized CC approaches adopting a hop-by-hop model where all nodes along a network path can be involved in the procedure. Each node should make decisions based only on local information since none of them has complete knowledge of the system state.

Previous work on CC involving mathematical models of population biology was proposed for the Internet on the basis of either improving the current TCP CC mechanism [6] or providing a new way of combating congestion [7]. The study of [6] couples the interaction of Internet entities that involved in CC mechanisms (routers, hosts) with the predator-prey interaction. This model exhibits fairness and acceptable throughput but slow adaptation to traffic demand. Recent work by [7] focuses on a new TCP CC mechanism based on the LV competition model [8], [9] which is applied to the congestion window updating mechanism of TCP. According to the authors, remarkable results in terms of stability, convergence speed, fairness and scalability are exhibited. However, these approaches are based on the end-to-end model of the Internet, which is completely different from the hop-by-hop nature of ADNs. **The novelty of our approach lies in the fact that the LV model is applied to WSNs in a hop-by-hop manner**.

3 Autonomous Decentralized Networks: An Ecosystem View

An ADN (Fig. 1) is considered to be analogous to an ecosystem. An ecosystem comprises of multiple species that live together and interact with each other as well as the non-living parts of their surroundings (i.e. resources) to meet their needs for survival and coexist. Similarly, an autonomous network consists of a large number of cooperative nodes. Each node has a buffer in order to store packets and is able to initiate a traffic flow. All traffic flows compete with each other for available network resources in an effort to reach one or more sink nodes by traversing a set of intermediate nodes forming a multi-hop path. Just as in an ecosystem, *the goal is the coexistence of flows*.

To investigate the decentralized and autonomic nature of our approach, a network is divided into smaller neighborhoods called sub-ecosystems. Each sub-ecosystem involves all nodes that send traffic to a particular one-hop-away node. The traffic flows initiated by those nodes play the role of competing species and the buffer (queue) capacity of the receiving node can be seen as the limiting resource within the sub-ecosystem.

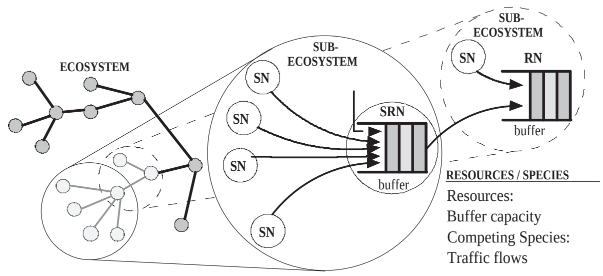


Fig. 1. Competition in AD networks.

Within a virtual ecosystem, participant nodes may perform different roles. In particular, each node is able to either initiate a traffic flow i.e. is a source node (SN), or serve as a relay node (RN) for multiple other flows, or perform both roles being a source-relay node (SRN). Source nodes are basically located at the edges of a network (e.g. leaf nodes) while relay nodes are internal nodes (e.g. backbone nodes). Our strategy provides hop-by-hop rate adaptation by regulating the traffic flow rate at each sending node. *Each node is in charge of self-regulating and self-adapting the rate of its traffic flow i.e., the rate at which it generates or forwards packets. All flows compete for available buffer capacity at their one-hop-away receiving node*. Each sending node is expected to regulate its traffic flow rate in a way that limiting buffer capacities at all receiving nodes along the network path towards the sink are able to accommodate all received packets. The sending rate evolution of each flow will be driven by variations in buffer occupancies of relay nodes along the network path towards the sink. Due to the decentralized nature of our approach, each node will regulate its traffic flow rate using local information (i.e. from neighbors). The number of bytes sent by a node within a given period refers to the population size of its flow. From an ecosystem perspective, the population size of each traffic flow (i.e. of each species) is affected by interactions among competing flows (species) as well as the available resources (buffers) capacities.

The proposed strategy is based on *a deterministic competition model which involves interactions among species that are able to coexist, in which the fitness of one species is influenced by the presence of other species that compete for at least one limiting resource*. Competition among members of the same species is known as intra-specific competition, while competition between individuals of different species is known as inter-specific competition. One of the most studied mathematical models of population biology, the LV competition model [8], [9], exhibits this behavior. The generalized form of an n-species LV system is expressed by a system of ordinary differential equations:

$$\frac{dx_i}{dt} = r_i x_i \left[1 - \frac{\beta_i}{K_i} x_i - \frac{1}{K_i} \left(\sum_{j=1, j \neq i}^{n} \alpha_{ij} x_j \right) \right], \quad (1)$$

for $i = 1, ..., n$, where $x_i(t)$ is the population size of species i at time t ($x_i(0) > 0$), r_i is the intrinsic growth rate of species i in the absence of all other species, β_i and α_{ij} are the intra-specific and the inter-specific competition coefficients respectively. In the classical LV model, the intra-specific competition coefficient β is always equal to one. The reason for this is explained in [4]. Also K_i is the carrying capacity of species i i.e., the maximum number of individuals that can be sustained by the biotope in the absence of all other species competing for the same resource. If only one resource exists and all species (having the same carrying capacity K) compete for it, then K can be seen as the resource's capacity. Next we will build on this model to develop our strategy.

4 Nature-inspired Approach

This section distinguishes the roles of the different entities (i.e., SN, RN, and SRN) involved in the congestion avoidance mechanism along the path towards a sink.
Source Node (SN) : Pure source nodes (SNs) are end-entities (Fig. 2) which are attached to the rest of the network through an downstream node e.g., a relay node (RN), or a source-relay node (SRN) located closer to the sink.

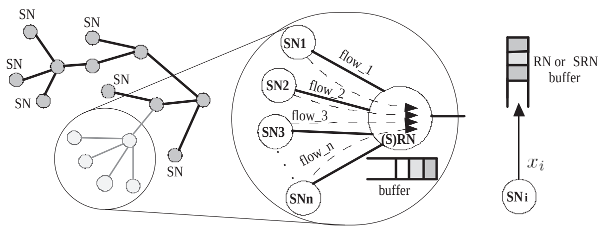


Fig. 2. Source nodes competing for a limiting resource at their downstream node.

Each SN is expected to initiate a traffic flow when triggered by a specific event. The transmission rate evolution of each flow is regulated by the solution of Eq. 1 (see Eq. 2) that gives the number of bytes sent x_i by flow i. In order to be able to solve Eq. 1 for a single node i, it is necessary to be aware of the aggregated number of bytes sent from all other nodes $\sum_{j=1,j\neq i}^{n} x_j$ which compete for the same resource. This quantity is denoted by C_i. In decentralized architectures, the underlying assumption of C_i-awareness is quite unrealistic. However, each SN can indirectly obtain this information through a small periodic backpressure signal sent from its downstream SRN/RN (father node) containing the total number of bytes sent from all father's children, denoted by BS. Each node can evaluate its neighbors' contribution C_i by subtracting its own contribution x_i from the total contribution BS as expressed by: $C_i = \sum_{j=1,j\neq i}^{n} x_j = BS - x_i$. Thus, Eq. 1 becomes:

$$\frac{dx_i}{dt} = rx_i\left(1 - \frac{\beta}{K}x_i - \frac{\alpha}{K}C_i\right),\ i = 1, ..., n. \tag{2}$$

To obtain x_i Eq. 2 is integrated :

$$x_i(t) = \frac{wx_i(0)}{\beta x_i(0) + [w - \beta x_i(0)]\, e^{-\frac{wr}{K}t}},\quad w = K - \alpha C_i \tag{3}$$

The validity of Eq. 3 is based on the assumption that $K - \alpha C_i > x_i$. If we set $\alpha = 1$ then, according to the inequality, the number of bytes sent from each node i (i.e. x_i) must not exceed the empty space left on the upstream node's buffer ($K - C_i$) so as to prevent buffer overflows. If we let K be a constant, the larger the value of α the smaller the value of x_i compared to the available buffer capacity of the upstream node.

According to [4], a network (ecosystem) of flows (species) that compete for a single resource while the populations of bytes sent are regulated by Eq. 3 has a global non-negative and asymptotically stable equilibrium point when inter-specific competition is weaker than intra-specific competition i.e., $\beta > \alpha$ ($\alpha, \beta > 0$). Under this condition, the series of values generated by each SN converges to a global and asymptotically stable *coexistence solution* given by Eq. 4. For a detailed proof of this concept refer to [4].

$$x_i^* = \frac{K}{\alpha(n-1) + \beta},\ i = 1, ..., n. \tag{4}$$

In order to avoid buffer overflows, it needs to be ensured that when a system of n active nodes converges to the coexistence solution, each node i will be able to send less than or equal to K/n bytes. This is satisfied by Eq. 4 when $\alpha(n-1) + \beta \geq n$ or $\beta - \alpha \geq n * (1 - \alpha)$. If we set $\alpha \geq 1$ and require $\beta > \alpha$ (equilibrium stability condition), then the aforementioned inequality is always satisfied.

Each SN evaluates Eq. 3 in an iterative manner. By iterative, we mean, roughly, that Eq. 3 generates a series of values which correspond to number of bytes sent every period T. The iterative form of Eq. 3 is expressed by:

$$x_i((k+1)T) = \frac{w(kT)x_i(kT)}{\beta x_i(kT) + [w(kT) - \beta x_i(kT)]\, e^{-\frac{w(kT)r}{K}T}} \tag{5}$$

Relay Node (RN) : Pure relay nodes (RNs) are internal entities which do not generate any packets, but forward packets belonging to several flows traversing themselves which

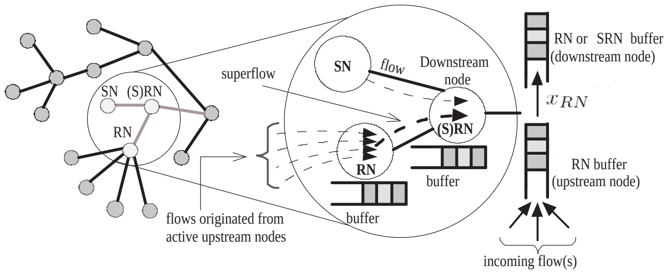


Fig. 3. Relay node creates a superflow which competes for downstream node's buffer.

compete for their resources. The main function of a RN is to combine (or multiplex) all incoming flows into a superflow and relay it to the dedicated downstream node (SRN or RN) as shown in Fig. 3. However, the superflow competes with other flows destined to the same downstream node (e.g., the flow originating from SN in Fig. 3). Hence, each RN is in charge of acting on behalf of all active upstream nodes whose flows are passing through it when evaluating the transmission rate of the superflow (i.e. number of bytes sent from RN within period T). As shown in Fig. 3, each one of the four flows of the superflow as well as the flow originating from SN should be able to allocate equal share of the downstream node's limiting resource. Thus, each RN allocates resources for its active upstream nodes based on a slightly modified expression of Eq. 5 as follows:

$$x_{RN}((k+1)T) = m\left(\frac{w(kT)H(kT)}{\beta H(kT) + [w(kT) - \beta H(kT)]\, e^{-\frac{w(kT)r}{K}T}}\right), \quad (6)$$

where $H(kT) = \frac{x_{RN}(kT)}{m}, w(kT) = K - \alpha C^*_{RN}(kT)$ and m is the total number of active upstream nodes which belong to the tree having RN as root. The number of bytes sent from a superflow within a period kT, namely $x_{RN}(kT)$, is equal to the aggregated number of bytes sent from m RN's upstream source nodes which compete for RN's buffer. Each RN can calculate the number (m) of its active upstream nodes by examining the source id field of each packet traversing itself. $C^*_{RN}(kT)$ reflects the total number of bytes sent (BS) to the downstream node ((S)RN in Fig. 3) from all competing children nodes subtracting the contribution of a single flow belonging to the superflow. $C^*_{RN}(kT)$ can be expressed as $C^*_{RN} = BS - \frac{x_{RN}(kT)}{n}$.
Source-Relay Node (SRN) : A source-relay node (SRN) acts as both source and relay node, having both functions concurrently operated as described above.

5 Performance Evaluation

Simulation studies were used to investigate how parameters affect the performance of our mechanism in terms of sensitivity to parameters, scalability and global fairness.

As discussed above, the rates of all flows converge to a global and asymptotically stable solution when $\beta > \alpha$ ($\alpha, \beta > 0$). There is no upper limitation on β but as it becomes larger, the steady state traffic rate (Eq. 4) decreases. In this case, each node will have to transmit data at a lower rate leading to lower quality of the received streams at the sink. As far as r is concerned, the system of Eq. 1 has a stable equilibrium point for any value of $r > 0$ [4], [14]. An upper bound for r is not analytically known, thus can be experimentally explored. The mathematical analysis of our model gives a general understanding of the system's behavior on the basis of stability as function of the α and β. However, the complexity of an ADN necessitates simulation evaluation using plausible scenarios that cannot be formally tested. The analytical study serves as the basis for the simulations.

In order to supplement the analytical results, some simulation experiments were conducted both in Matlab and in NS2. We considered a wireless sensor network consisting of 25 nodes which are deployed in a cluster-based topology (Fig. 4). Our mechanism was evaluated in a static and failure-free environment. All nodes were assumed to have the same buffer capacity $K = 35$KB. The time period T between successive evaluations of the number of bytes sent by each SN, as well as the time between backpressure signals was set to 1 sec. It was assumed that nodes 5, 6, 10, 14, 16 and 20 were activated at $1T$, $50T$, $150T$, $300T$, $450T$, $600T$ and 900 respectively. Node 14 was deactivated at $750T$. **Stability and Sensitivity**: Based on the analytical study of our model [4], the

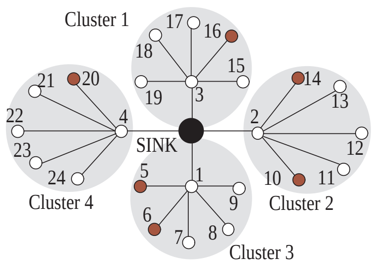
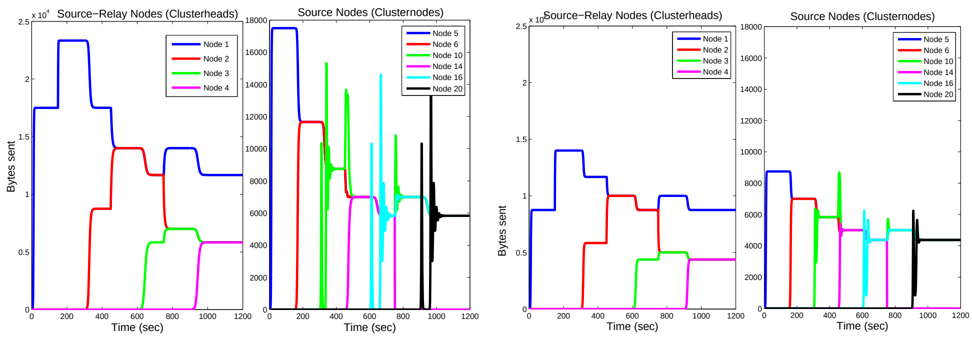


Fig. 4. Experimental cluster-based topology (all links are wireless).

satisfiability of some conditions contributes to system's stability. Their validity was further investigated by simulating complex scenarios that cannot be formally tested. It has been mathematically proved that if $\beta > \alpha$, then all sending rates converge to a stable equilibrium value $\forall r$ (detailed proofs in [4]). Initially, α and r were set equal to 1 while the value of β varied.

Fig. 5(a) depicts the estimated number of bytes that can be sent per T from each active node when $\beta = 2$. As can be observed, the system was able to re-converge to a new stable point after a change in network state (node activation). However, fluctuations in sending rates arose when (previously inactive) downstream nodes were not prepared to accommodate the increasing incoming traffic before Eq. 6 converged. This behavior was exhibited by flows initiated from nodes 10, 16 and 20. These flows were not well behaved but exhibited some oscillatory behavior after changes in network state. Also, some fluctuations occurred when the flow of node 14 was deactivated. Note that buffer

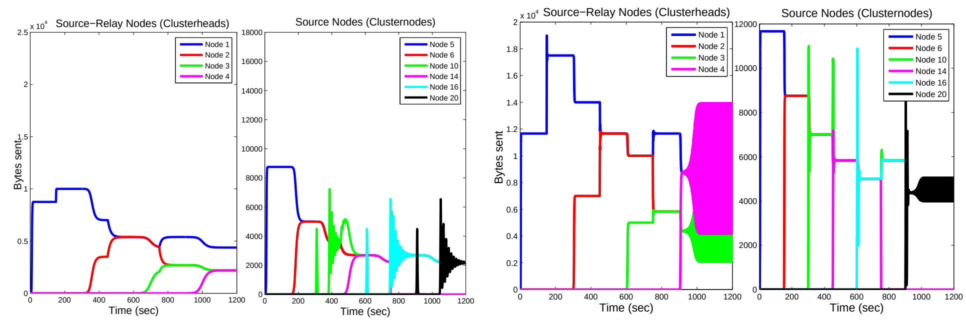


(a) (b)

Fig. 5. Estimated bytes sent/sec: (a) $\beta = 2$, (b) $\beta = 4$, when $\alpha = 1$ and $r = 1$.

overflows never occurred since the amount of traffic that was sent by each flow was small compared with the downstream node's buffer capacity.

When β increased to 4 (Fig. 5(b)) all flows became well-behaved while some small oscillations occurred as a result of changes in network state. Even though there is no upper bound for β value, it is worth pointing out that as β increases, the equilibrium value decreases (see Eq. 4) and the quality of the received data at the sink may be reduced. Increasingly, the results of Fig. 5(a) and (b) suggest that β should be greater than α but greater enough (this may depends on n) such that each node can allocate much less than K/n. This observation is supported by Fig. 6(a) ($\alpha = 3, \beta = 4$). When β is much greater than α, high buffer utilization is prevented, while smooth and stable response of traffic flows is achieved. In all the previous scenarios, the parameter r was set to 1. Further simulation studies were carried out in order to study the influence of r on stability. Results showed that the stability of traffic flows rates depends on r but a different behavior was observed with the change in parameters α and β. In general,



(a) (b)

Fig. 6. Estimated bytes sent/sec: (a) $\alpha = 3, \beta = 4, r = 1$, (b) $\alpha = 1, \beta = 3, r = 4$.

it was shown that the flow sending rates converged when $r \leq 2.5$ for quite a large number of combinations of α and β values. Therefore, r could not grow unboundedly but smooth network operation could be preserved in low r values (≤ 2.5). Fig. 6(b) illustrates large fluctuations in flow sending rates occurred for $\alpha = 1, \beta = 3, r = 4$.

Scalability and Fairness: The system proved to be adaptable against changing traffic load and achieved scalability by sharing buffer capacity of nodes to their active up-stream nodes. For example in Fig. 5(b), in the presence of one sender (node 5) the stable equilibrium point of the system given by Eq. 4 was 8750 bytes/T (clusterhead node 1 transmitted at the same rate). When node 6 became active, each sender obtained 7000 bytes/T, while the downstream node 1 (clusterhead) was able to accommodate both senders by increasing its rate using Eq. 6. When the number of senders scaled up, all senders could be supported by the system by diminishing the sending rate per node, thus offering graceful degradation. Fairness was also achieved having the available buffer capacity of each node equally shared among all activated flows.

Further simulations were conducted using the discrete event based simulator NS2 in order to evaluate the performance of the LVCC mechanism under more realistic network conditions (in terms of packet loss and delay) when multiple users are involved. Performance was measured in terms of the packet delivery ratio (PDR), which is defined as the ratio of the total number of packets received by the sink to the total number of packets transmitted by source nodes. The following table presents the combinations of α and β values ($r = 1$) that achieved the highest transmission rates (bytes sent per T) and the highest mean PDR for different number of active nodes. It is worth pointing out that only the scenarios where traffic flows of all active nodes converged to stable solutions were taken into consideration.

Table 1. Performance evaluations for realistic network conditions using NS2 [5].

α	β	*No. of Active Nodes*	*Mean Packet Delivery Ratio*
1.6	3.3	3	0.99
1.5	4.5	5	0.99
1.7	6.0	7	0.88
1.4	6.2	10	0.70
1.6	6.5	15	0.64
1.9	6.5	20	0.62

The results of Table 1 support previous results obtained from Matlab simulations. It can be seen that as the number of active nodes scaled up, stable response of traffic flows was achieved with the increase of parameter β. On the other hand, α remained from 1.5 to 1.9 regardless of the number of active nodes. In addition, the mean PDR decreased below 70% when more than 10 active nodes were concurrently activated in the topology of Fig. 4. This is due to the fact that the network resources (e.g. wireless channel capacity) were incapable of sustaining such a large number of active nodes, resulting in high packet losses.

6 Conclusions and Future Work

This study investigates how nature inspired models can be employed to prevent congestion in ADNs. Inspiration from biological processes is drawn where global properties e.g., self-adaptation and scalability are achieved collectively without explicitly programming them into individual nodes, using simple computations at the node level.

Motivated by the famous LV competition model, a rate-based, hop-by-hop CC mechanism (LVCC) was designed which aims at controlling the traffic flow rate at each sending node. Simulations were performed to understand how the variations of the model's parameters influence stability and sensitivity. Simulation studies validated the correctness of analytical results of [4] and showed that our model achieves scalability, graceful performance degradation, adaptability and fairness. Realistic scenarios of network operation were also taken into consideration. However, for future work, further simulations for generalized network cases are required. Also a study of the behavior of our mechanism is needed when dynamic network conditions in terms of offered traffic load and node failures are considered.

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