Biologically Inspired Networking and Sensing:

Algorithms and Architectures

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Chapter 9
Congestion Control in Wireless Sensor Networks Based on the Lotka Volterra Competition Model

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ABSTRACT

Next generation communication networks are moving towards autonomous wireless infrastructures, as for example, Wireless Sensor Networks (WSNs) that are capable of working unattended under dynamically changing conditions. Over the last few years, WSNs are being developed towards a large number of multimedia streaming applications, e.g., video surveillance, traffic control systems, health monitoring, and industrial process control. However, WSNs face important limitations in terms of energy, memory and computational power. The uncontrolled use of limited resources in conjunction with the unpredictable nature of WSNs in terms of traffic load injection, wireless link capacity fluctuations and topology modifications (e.g. due to node failures) may lead to congestion. Congestion can cause deterioration of the offered quality of service (QoS). This study proposes a bio-inspired congestion control approach for WSNs streaming applications that necessitate controlled performance with graceful degradation. The proposed approach prevents congestion by regulating the rate of each traffic flow based on the Lotka-Volterra competition model. Performance evaluations reveal that the proposed approach achieves adaptability to changing traffic loads, scalability and fairness among flows, while providing graceful performance degradation as the offered load increases.

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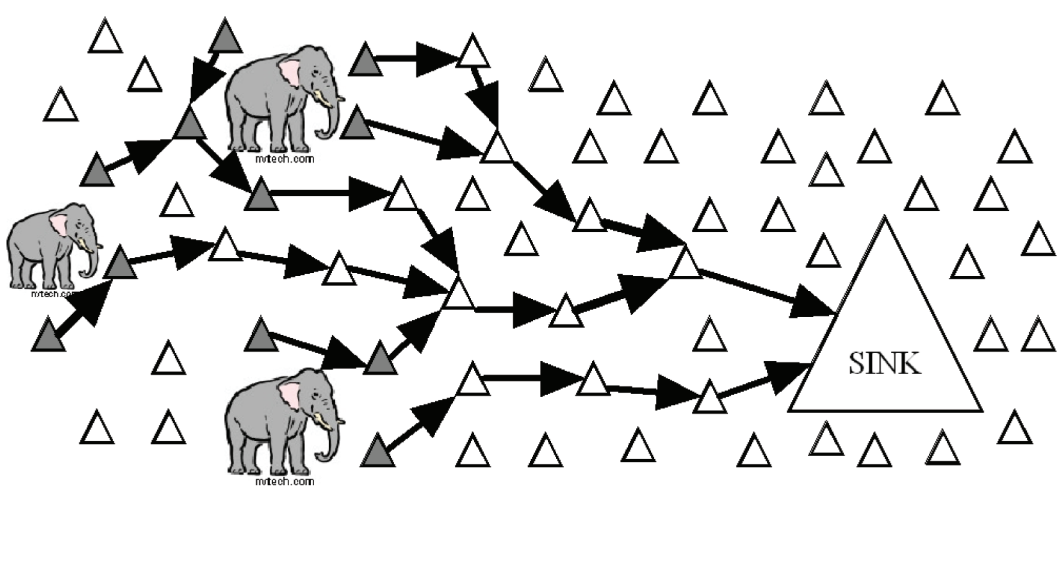
INTRODUCTION

Rapid technological advances and innovations in the area of autonomous systems push the vision of Ambient Intelligence from concept to reality. Networks of autonomous wireless 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. Wireless Sensor Networks (Akyildiz, 2002), can be used as platforms for health monitoring, battlefield surveillance, environmental observation, industrial control etc.

Despite the utmost importance of performance control, this issue has not been given enough attention from the research community. One of the main reasons is that research on WSNs has been heavily influenced by military applications in which dense, large-scale networks of sensors are expected to be deployed in a random manner, primarily with a view to tracking objects. However, most of the aforementioned critical applications necessitate small-scale networks with planned deployment of sensors close to selected locations/objects of interest in order to achieve controlled performance. The proposed approach is designed on the basis of providing performance control for critical applications in small-scale WSNs.

Typically, WSNs consist of small, cooperative devices (nodes) which may be constrained by computation capability, memory space, communication bandwidth and energy supply. However, with the rapid development of low-cost hardware CMOS cameras and microphones, autonomous sensor devices are becoming capable of ubiquitously retrieving multimedia content such as video and audio streams from the environment. This new and emerging type of sensor network, the so-called Wireless Multimedia Sensor Network (WMSN), has drawn the immediate attention of the research community (Akyildiz, 2007). As shown in Figure 1, a number of nodes that at a particular moment sense an event (grey-shaded nodes), can send streaming data through the network, in a multi-hop manner, to a dedicated sink node. Alternatively, some nodes may be constantly sending streaming data to the sink. The unpredictable nature of traffic load injected into the network as well as the uncontrolled use of the scarce network resources (buffer size, wireless channel capacity) are able to provoke *congestion*. Thus, there is an increased need to design novel congestion control strategies

Figure 1. A WSN for wildlife monitoring



possessing self-* properties like self-adaptability, self-organization as well as scalability, and fairness, which are vital to the mission of dependable multimedia WSNs.

The focal point of this study is to propose a *scalable and self-adaptive bio-inspired congestion control mechanism* targeting streaming applications in WSNs for delivering enhanced application fidelity at the sink (in terms of packet delivery ratio and delay) under varying network conditions. More specifically, the *main objective is to provide efficient and smooth rate allocation and control while maintaining fairness and friendliness with interfering flows*. Biological processes which are embedded in decentralized, self-organizing and adapting environments, provide a desirable basis for computing environments that need to exhibit such properties.

Simple mathematical biology models (Brauer, 2000) 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. This study focuses on the Lotka-Volterra (LV) competition model, and proposes a decentralized approach that regulates the rate of every flow in order to prevent, or at least gracefully minimize congestion. The LV-based congestion control (LVCC) mechanism targets small-scale dependable multimedia WSNs (Akyildiz, 2007) and especially for applications that require continuous stream of data. The LV competition model was also applied in modifying the congestion control mechanism of TCP (Hasegawa, 2006). However, *the novelty of our approach lies in the fact that the LV model is applied to WSNs in a hop-by-hop manner*.

Based on analytical evaluations performed in Antoniou (2007), the LVCC model guarantees that the equilibrium point of the system ensures coexistence of all flows, with stability and fairness among active flows under certain conditions. In this paper, the validity of the analytical results is further investigated by simulating complex scenarios that cannot be formally tested. Performance evaluation results showed that the LVCC approach can provide adaptation to dynamic network conditions as well as scalability, fairness and graceful performance degradation among traffic flows when multiple active nodes are involved.

The remainder of this paper is organized as follows. Section 2 deals with the problem of congestion in WSNs, discusses conventional congestion control techniques for WSNs, and introduces the Lotka-Volterra (LV) competition model. Section 3 presents the analogy between WSNs and ecosystems in nature. Section 4 proposes the LV-based Congestion Control (LVCC) mechanism. Section 5 evaluates the performance of our mechanism in terms of stability, scalability and fairness. Section 6 presents future research directions, while Section 7 draws the conclusion.

BACKGROUND

Congestion in WSNs

Congestion occurs when the traffic load injected into the network exceeds available capacity at any point of the network. In wireless networks, packet losses can be attributed to either *buffer overflows*, or *collisions in the wireless medium* when more than one nodes are trying to access the channel simultaneously. The problem of buffer overflows is considered to be more critical in WSNs due to buffer size limitations. In addition, the existence of a proper medium access control (MAC) protocol, e.g. based on CSMA (Carrier Sense Multiple Access) or TDMA (Time Division Multiple Access), is expected to minimize (CSMA) or resolve (TDMA) the wireless medium contention.

Buffer overflows at a sensor node are caused when the incoming traffic load exceeds the outgoing traffic load. In this case, accumulated packets overwhelm buffer capacity. Even at low traffic rates, buffer overflows can be experienced at some point of the network (usually close to the sink) due to the converging (many-to-one) nature of packets from multiple sending nodes to a single sink node. At the same time, wireless channel contention may cause packet loss. As contention becomes more intensive, the waiting time for obtaining the channel for transmission also increases. As a node waits for the channel, additional traffic may arrive filling up its buffer and further increasing packet delays. The discussion above indicates that congestion may cause multiple packet losses, low link utilization (throughput reduction), increase of queueing delays, leading to the deterioration of the offered quality of service (QoS). Increasingly, congestion in WSNs is responsible for energy waste, decrease of network lifetime and even for the decomposition of network topology in multiple components.

In traditional Internet wired networks, congestion control is usually applied in an end-to-end manner, i.e. only the source-destination pair is involved. However, end-to-end congestion control approaches will not be effective in the error-prone wireless multihop networks because the end-to-end nature may result in reduced responsiveness causing increased latency and high error rates, especially during long periods of congestion. In addition, the end-to-end model is not very effective for WSNs, where delivery of data to the sink, without retransmission of any lost packets, is the normal objective. Due to their severely constrained nature, WSNs necessitate autonomous, decentralized, fast time scale congestion control strategies which promise immediate, effective and efficient relief from congestion. Decentralized approaches are expected to adopt 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 (e.g. buffer load, channel load) since none of them has complete information about the system state. This is a desirable feature as it minimizes the exchange of messages, hence improves both energy and congestion.

Conventional Techniques for Congestion Control in WSNs

Early studies in the area of sensor networks had mainly focused on more fundamental networking problems, e.g. medium access control (MAC), topology, routing, and energy efficiency, and had largely ignored network performance assurances. Lately, with the emergence of mission-critical applications (e.g., health monitoring), there has been increased interest in performance control mechanisms, so as to avoid congestion caused by the uncontrolled use of the scarce network resources.

Various congestion control approaches can be found in WSNs literature based on traffic manipulation (e.g. rate adaptation to network changes CODA (Wan, 2003), Fusion (Hull, 2004), IFRC (Rangwala, 2006), ARC (Woo, 2001), multi-path routing BGR (Popa, 2006), CAR (Kumar, 2006), TADR (He, 2008)), topology control (e.g. clustering formation (Karenos, 2006)), and network resource management (e.g. power control, multiple radio interfaces Siphon (Wan, 2005)). Rate control approaches are considered to be the most appropriate when dealing with streaming applications. Rate control is a common technique for alleviating congestion by throttling the injection of traffic in the network.

Some of the rate-based CC schemes CODA (Wan, 2003), IFRC (Rangwala, 2006), ARC (Woo, 2001) and BGR (Popa, 2006) are based on traditional methodologies and protocols known from the Internet, for example, the Additive Increase Multiplicative Decrease (AIMD) rate control mechanism. AIMD uses packet loss as indication of congestion, i.e. increases rate until packet loss and then decreases rate in a multiplicative way.

However, this model is not very effective in WSNs because it provokes a saw-tooth rate behavior which may violate the QoS requirements (e.g. fidelity of a stream). Also the increase of rate until packet loss seems to be inefficient since it may drive a network into congestion, causing high queueing delays. In addition, AIMD-like mechanisms take a long time for data rates to converge in low-rate wireless links, which would cause significant variation in streaming media quality. The proposed mechanism was found to outperform AIMD (see Section 5), providing smooth rate allocation and control while maintaining friendliness among competing flows.

The Lotka-Volterra Competition Model of Mathematical Biology

Non linear systems are often studied in terms of simple mathematical biology models (Brauer, 2000) which aim at modeling natural and biological processes using analytical techniques. Population dynamics has traditionally been the dominant branch of mathematical biology which studies how populations of species change in time and space as well as the processes that cause these changes. Information about population dynamics is of fundamental importance for policy making and planning as, for example in designing a congestion avoidance policy.

Population dynamics can be modeled with a simple balance equation that describes how the overall population size of a species changes from time to time as a result of species interaction with resources, competitors, mutualists and natural enemies. In particular, mathematical models of competition, mutualism and predator-prey which are among the most studied problems in population dynamics for multiple species can be expressed as a set of parameterized difference or differential equations, or dynamical systems. These mathematical models can be divided into two categories, namely, deterministic and stochastic population models. Deterministic population models play a dominant role in the global behavior investigation of large-scale problems in population dynamics, since they allow much more rigorous and detailed investigation of the model potential compared with stochastic population models.

Deterministic models specify a unique dy namic path of the system called trajectory determined by initial conditions.

The proposed approach 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. An in depth investigation and modeling of competitive interactions between organisms provides an initial basis for predicting outcomes since they may influence species evolution, the structuring of communities (i.e. which species coexist, which die out), and the distributions of species.

One of the most studied mathematical models of population biology, the Lotka Volterra (LV) competition model (Lotka, 1925), (Volterra, 1931), exhibits this behavior. The generalized form of an *n*-species LV system is expressed by a system of ordinary differential equations:

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

for $I = 1,\ldots,n$, where $x_i(t)$ is the population size of species i at time t, r_i is the intrinsic growth rate of species i in the absence of all other species, βi and αi_j are the intra-specific and the inter-specific competition coefficients respectively. 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 approach.

Previous work on congestion control involving mathematical models of population biology was proposed for the Internet on the basis of either improving the current TCP CC mechanism (Analoui, 2006) or providing a new way of combating congestion (Hasegawa, 2006). The study of Analoui (2006) 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 Hasegawa (2006) focuses on a new TCP CC mechanism based on the LV competition model 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 WSNs. *The novelty of our approach lies in the fact that the LV model is applied to WSNs in a hop-by-hop manner*.

WIRELESS SENSOR NETWORKS: AN ECOSYSTEM VIEW

A WSN 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, a wireless sensor network involves a number of cooperative nodes. Each node has a buffer in order to store packets and is able to initiate a traffic flow. Traffic flows can be seen as species that compete with each other for available network resources while traversing a set of intermediate nodes forming a multi-hop path leading to the sink. The number of bytes per traffic flow corresponds to the population size of each traffic flow. In analogy with ecosystems, *the goal is expected to be the coexistence of flows*. In the rest of the paper, the terms flows and species are used interchangeably.

To investigate the decentralized and autonomic nature of the proposed 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 (parent node). *The traffic flows initiated by each node play the role of competing species and the buffer (queue) capacity of the parent node can be seen as the limiting resource within the sub-ecosystem*.

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) to forward packets of multiple flows passing through it, or perform both roles being a source-relay node (SRN). Source nodes are mostly located at the edges of a network (e.g. leaf nodes) while relay nodes are internal nodes (e.g. backbone nodes). The proposed approach provides hop-by-hop rate adaptation by regulating the traffic flow rate at each 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. The traffic flows compete for available buffer capacity at their one-hop-away receiving node involved in the path leading to the sink*. As shown in *Figure 2*, the traffic flow *5* (initiated by SRN) is composed of traffic flows *1-4*. 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 the proposed approach, thus satisfying the need for low communication overhead, each node will regulate its traffic flow rate using local information (i.e. from one-hop away neighbors). As mentioned before, 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 LV-based Congestion Control (LVCC) Approach

This section distinguishes the roles of the different entities (SN, RN, and SRN) involved in the congestion avoidance mechanism along the path towards a sink.

Source Node (SN)

As shown in *Figure 3*, pure source nodes (SNs) are end-entities which are attached to the rest of the network through a downstream node e.g., a relay node (RN), or a source-relay node (SRN) located closer to the sink.

Each SN is expected to initiate a traffic flow when triggered by a specific event. The transmission rate evolution of each flow is calculated by Equation 2 (the solution of Equation 1) that gives the number of bytes sent x_i by flow *i*. In order to be able to solve Equation 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 (parent node) containing the total number of bytes sent from all parent'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, Equation 1 becomes:

Figure 2. Traffic flows competition in WSNs

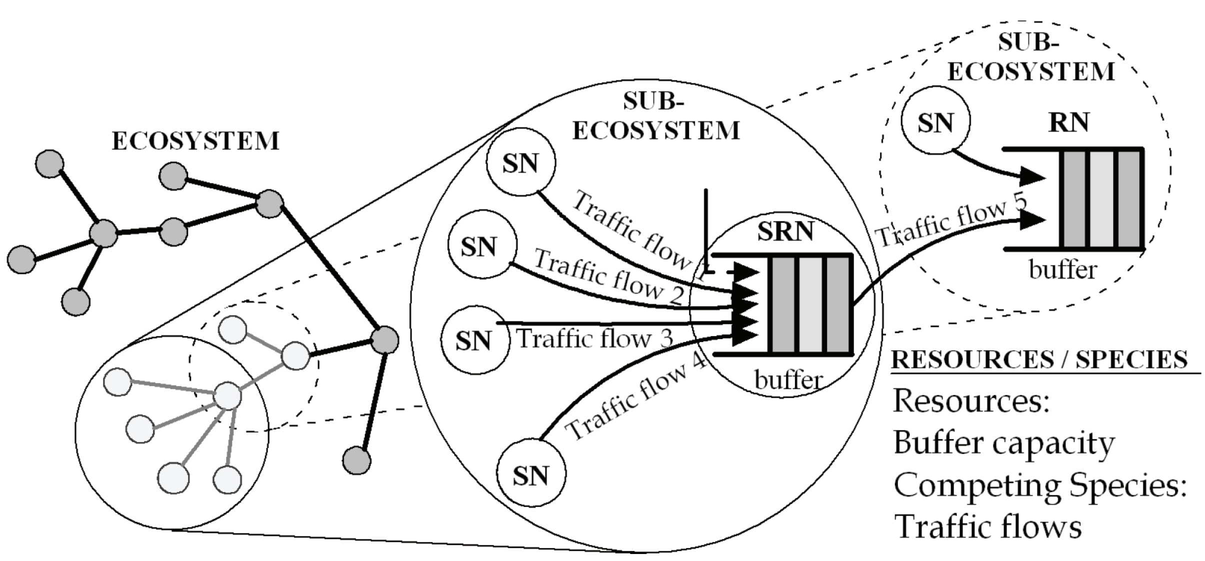
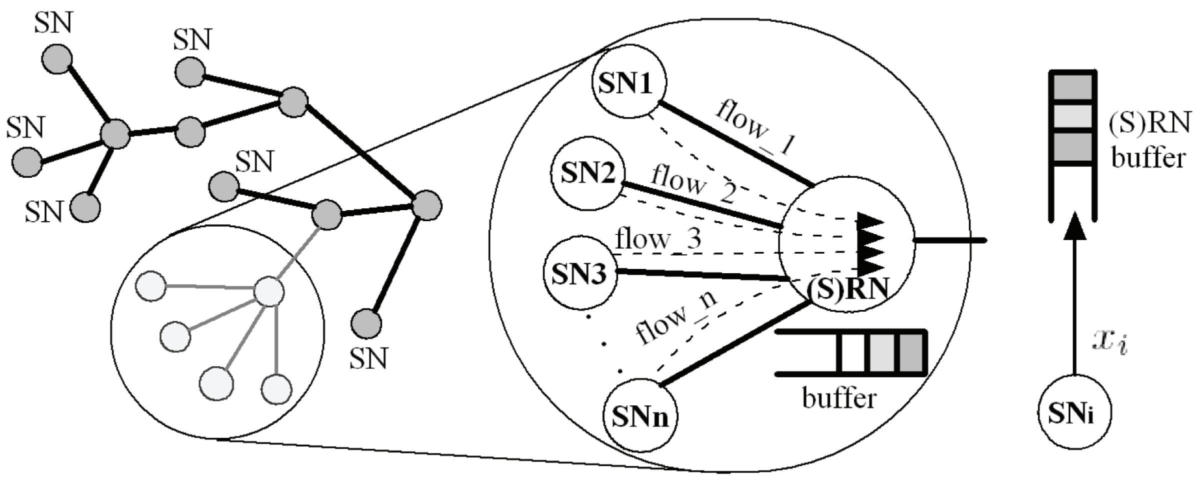


Figure 3. Source nodes competing for a limiting resource at their downstream node



$$\frac{dx_i}{dt} = rx_i\left[1 - \frac{\beta}{K}x_i - \frac{1}{K}C_i\right], \quad i = 1,...,n. \tag{2}$$

Equation 2 is integrated to obtain the calculated transmission rate of each SN, x_i, given by:

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

A recent study by Antoniou (2007) focused on a network (ecosystem) of flows (species) competing for a resource, where the populations of flows (number of bytes sent) are regulated by Equation 3. It was found that such a network has a global non-negative and asymptotically stable equilibrium point when inter-specific competition is weaker than intra-specific competition i.e.,$\beta > \alpha$ *a*nd α, $\beta > 0$. Under this condition, the series of values generated by each SN converges to a global and asym*ptotically stable coexistence solution giv*en by Equation 4. For a detailed proof of this concept refer to \cite{Antoniou}.

$$x_i^* = \frac{K}{\alpha\left[n-1\right] + \beta}, \quad i = 1,...n. \tag{4}$$

Furthermore, 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 Equation 4 when $\alpha[n-1] + \beta > n$ or β-α >**n**[1- α]. *If* we set α >1 a*nd* require $\beta > \alpha$ (*as* im*po*sed by the equilibrium stability condition), then the aforementioned inequality is always satisfied. Therefore, to ensure both convergence and no buffer overflows the following two conditions must be satisfied:

$$\beta > a, \quad a > 1. \tag{5}$$

The calculated transmission rate of each node, xi(t), *i*s *i*nitiated by xi(0) *a*n*d c*onverges to the stable coexistence solution, xi* wi*t*h*i*n time Tconv. *The* convergence time, Tconv, *can* be evaluated by setting xi(Tco*n*v*)* = *xi** (o*n t*he basis of Equation 3) and is found to be proportional to parameter α and *in*versely proportional to parameters r. This observation practically means that fast convergence can be achieved using small values of α or large values of r, but further discussion is given in performance evaluations.

Each SN adjusts its transmission rate on the basis of Equation 3. This adjustment is carried out iteratively on a discrete-time basis, projecting the transmission rate from time t to some future time t+T (i.*e.* over a time period T). For example, at the beginning of the k+1-th *t*ime period, t = (k+*1*)T, *E*qua*t*ion 3 is used to obtain the new transmission rate by the following calculation: set (a) xi(0) to *the* previous calculated transmission rate xi(kT), (*b)* *t* to th*e* time duration T betwe*e*n the two successive transmission rate evaluations and (c) Ci to C*i* (kT) *i*.e. aggregate number of bytes sent from all competing nodes within the previous period. Therefore, Equation 3 can be expressed in an iterative form as follows:

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

Equation 6 generates a series of values which correspond to number of bytes sent every period T.

*R*elay Node (RN)

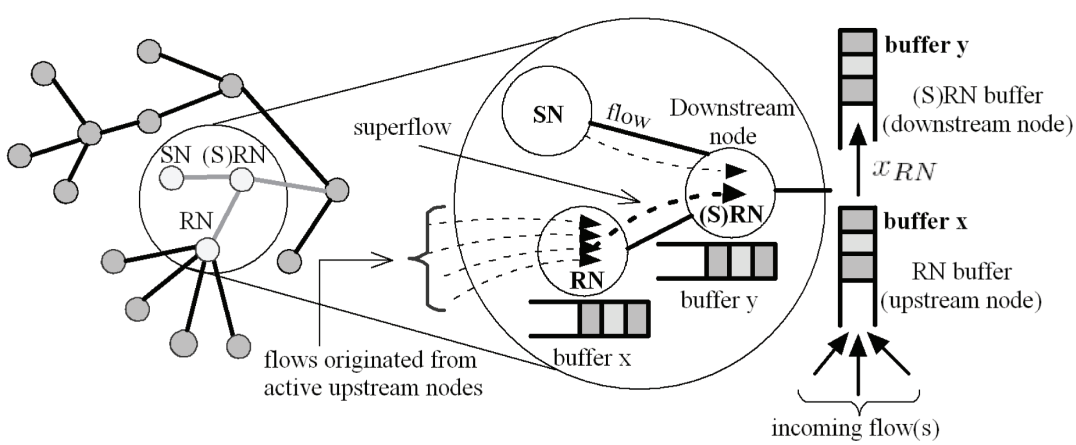
Pure relay nodes (RNs) are entities which do not generate any packets, but forward packets belonging to several flows traversing themselves which compete for their resources.

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 F*igure 4*. However, the superflow competes with other flows destined to the same downstream node (e.g., the flow originating from SN in F*igure 4)*. 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. As shown in F*igure 4,* each one of the four flows of the superflow as well as the flow originating from SN should be allocated equal share of the downstream node's limiting resource. Each RN allocates resources for its active upstream nodes based on a slightly modified expression of Equation 6 as follows:

$$x_{RN}\left(\left(k+1\right)T\right)=\frac{w\left(kT\right)H\left(kT\right)}{\beta H\left(kT\right)+\left[w\left(kT\right)-\beta x_i\left(kT\right)\right]e^{-\frac{w(kT)r}{K}T}}, \quad (7)$$

where *H(kT)* = x_{RN}*(kT)/m, w(kT)* = *K-α C*R*$_{N}$*(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 k*T,* x*R*$_{N}$*(kT)/,* should be equal to the ag-

Figure 4. Relay node creates a superflow which competes for downstream node's buffer



gregated number of bytes sent from m RN's upstream source nodes which compete for RN's buffer. Each RN can calculate the number of its active upstream nodes, m, by examining the source id field of each packet traversing itself. C*$R_{N(}kT)$ reflects the total number of bytes sent (B*S)* to the downstream node ((S)RN in F*igure 4)* from all its competing children nodes, subtracting the contribution of a single flow belonging to the superflow. C*$R_{N(}kT)$ can be expressed as:

$$C^{*}_{RN}\left(kT\right) = BS - \frac{x_{RN}\left(kT\right)}{m}. \tag{8}$$

If the calculated transmission rate of a superflow is less than the aggregated transmission rate of all incoming flows consisting the superflow, a number of packets is expected to be accumulated in buffer x. Thus, the available buffer capacity at buffer x will be progressively decreased causing upstream nodes to decrease their calculated sending rates. In this way, congestion phenomena can be prevented.

Source-Relay Node (SRN)

A source-relay node (SRN) acts as both source and relay node, having both functions concurrently operated as described above.

PERFORMANCE EVALUATION

This section evaluates the performance of the LVCC model and discusses the effectiveness of the model in preventing congestion by mimicking the species competition in nature. More specifically, control system type simulations (through Matlab) and realistic network simulations (using NS2 network simulator) were conducted to show the basic features of the proposed bio-inspired mechanism such as *self-adaptiveness, scalability and fairness*. In addition, evaluation studies investigate how parameters affect the performance of our mechanism in terms of *stability and convergence* and provide effective parameter setting on the basis of congestion-oriented metrics.

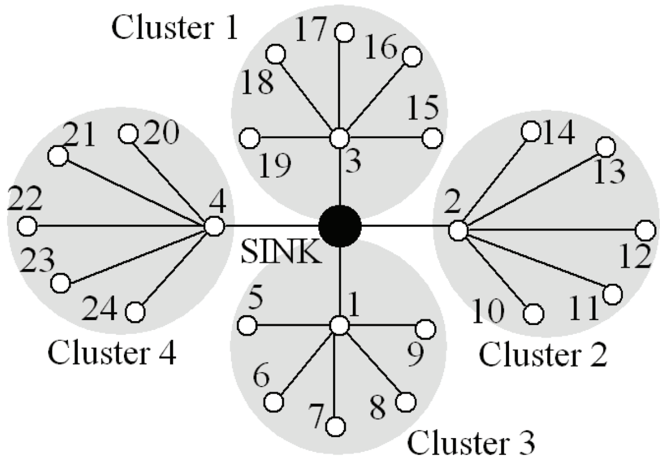
Analytical Results: The Basis

Based on analytical results about α and β, the calculated rates of all flows converge to a global and asymptotically stable solution when $\beta > \alpha$, and $\alpha > 1$ for avoiding buffer overflows. There is no upper limitation on β but as it becomes larger, the steady state traffic rate (Equation 4) decreases. In this case, each active node will be limited 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 Equation 1 has a stable equilibrium point for any value of $r > 0$ (Antoniou, 2007), (Takeuchi, 1980). An upper bound for r is not analytically known, thus will 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 parameters α and β. However, the complexity of WSNs necessitates simulation evaluation using plausible scenarios that cannot be formally tested. The analytical study serves as the basis for the simulations.

Simulation Studies: The Step Further

In order to supplement the analytical results, some simulation experiments were conducted both in Matlab (theoretical model analysis scenarios) and in NS2 (realistic network scenarios). We considered a wireless sensor network consisting of *25* wireless nodes which are deployed in a cluster-based topology (*Figure 5*). The proposed LVCC approach can be efficiently and effectively used on top of routing or MAC protocols that create small depth (< 4) cluster/treebased logical topologies over any physical topology. However, a detailed study of such protocols is beyond the scope of the current paper. In this study, a dedicated routing

Figure 5. Evaluation cluster-based topology of 25 nodes (all links are wireless)



protocol that creates the underlined topology was assumed. We used this type of topology so as to better understand and evaluate the behavior of our LV-based mechanism. The grey-shaded area represents a collision domain. For example, the nodes of cluster 1 (nodes 5, 6, 7, 8, and 9) will perceive each other's transmissions.

Theoretical Model Analysis Using Control System Type Simulations

The validity of analytical results in complex scenarios that could not be formally tested was further investigated in Matlab. It was assumed that nodes *5, 6, 10, 14, 16* and *20* were activated at *1T, 50T, 150T, 300T, 450T, 600T* and *900T* respectively. Node *14* was deactivated at *750T*. Each node buffer size was set to *K=35*KB.

Realistic Network Simulations

In addition, the proposed mechanism was evaluated in a realistic static and failure-free network environment, using a series of representative network operation scenarios under NS2 networking simulator. The two-ray ground radio propagation model was used in all experiments. The buffer capacity of each node was set to *35*KB. The time period *T* between successive evaluations of the calculated rate of each SN, as well as the time between backpressure control packets was set to *1* sec. The selection of *1* second is guided by the desire to maintain responsiveness to changes in the network state and to avoid overwhelming the network with control packets. The CSMA-based IEEE *802.11* MAC protocol with *1* Mbps transmission rate and an exponential backoff policy was assumed. *Table 1* summarizes all scenarios evaluated in NS2. In each scenario, the different sets of nodes were activated.

Based on the LV competition model, each node is able to calculate its transmission rate i.e., the number of bytes it can send per time unit. In realistic scenarios, we assumed that each node will transmit in one of *5* different levels namely, *1, 2, 4, 6,* and *8* Kbytes per *T=1* second, starting from *1* Kbytes/*T* (i.e. *8* Kbps). Each node can increase its flow (or stream) rate to an upper level rate when the calculated transmission rate (obtained by Equation 6) exceeds the specific upper level rate. Similarly, there should be a transition from the current level rate to a lower level rate when the calculated transmission rate falls below the current level rate but is above the lower level rate.

Table 1. Description of scenarios in NS2

Scenario	No. of active nodes	Active nodes
1	3	5, 6, 10
2	5	5, 6, 10, 13, 14
3	7	5, 6, 10, 12, 13, 14, 21
4	10	5, 6, 10, 11, 12, 13, 14, 18, 21, 24

Performance Measures

Two common performance measures for congestion control approaches were taken into account: the packet delivery ratio (PDR) and the end-to-end delay (EED). Packet delivery ratio 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. End to end delay is defined as the time taken for a packet to be transferred from a source node to the sink.

Verification of Stability and Convergence Time Through Control System Type Simulations

Matlab is a technical computing software that can be used for control system type simulations. In these simulations, realistic network conditions such as queueing delays and wireless channel collisions were not considered.

Initially, α and r were set equal to *1* while the value of β varied. *Figures 6-8* illustrate the results obtained using Matlab. *Figure 6* depicts the calculated number of bytes that can be sent per T from each active node when $\beta = 2$. Bear in mind that low α and β values result in high calculated transmission rates at equilibrium, x^*, evaluated by Equation 4. As can be observed, the system

Figure 6. Calculated transmission rate (bytes sent per sec.) when α =1, β = 2, r =1

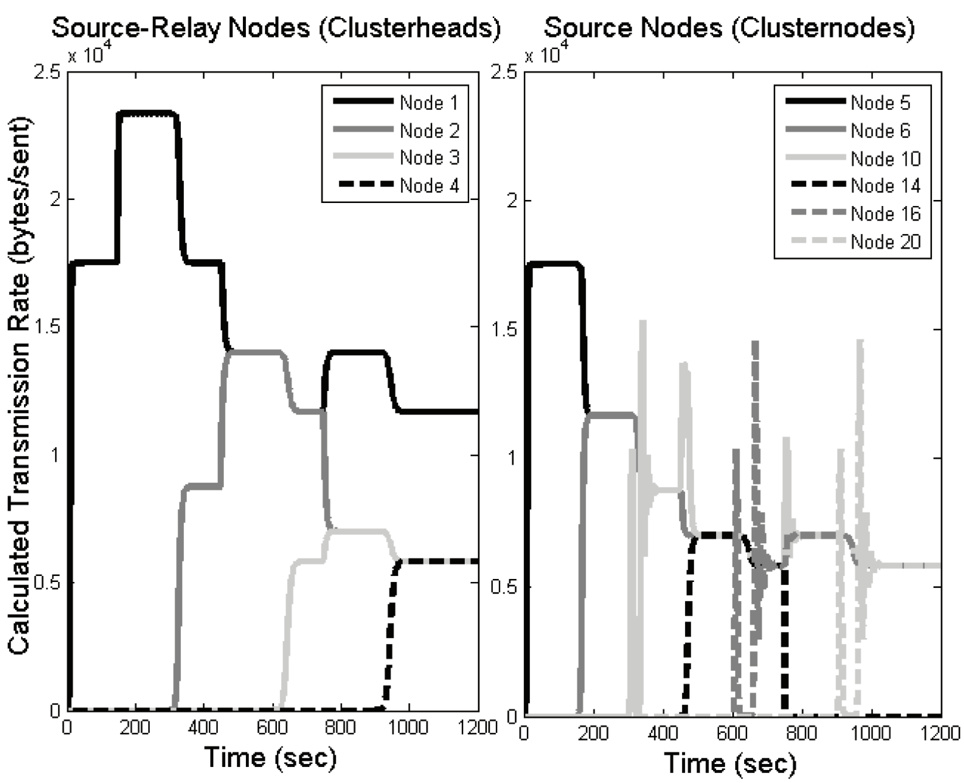
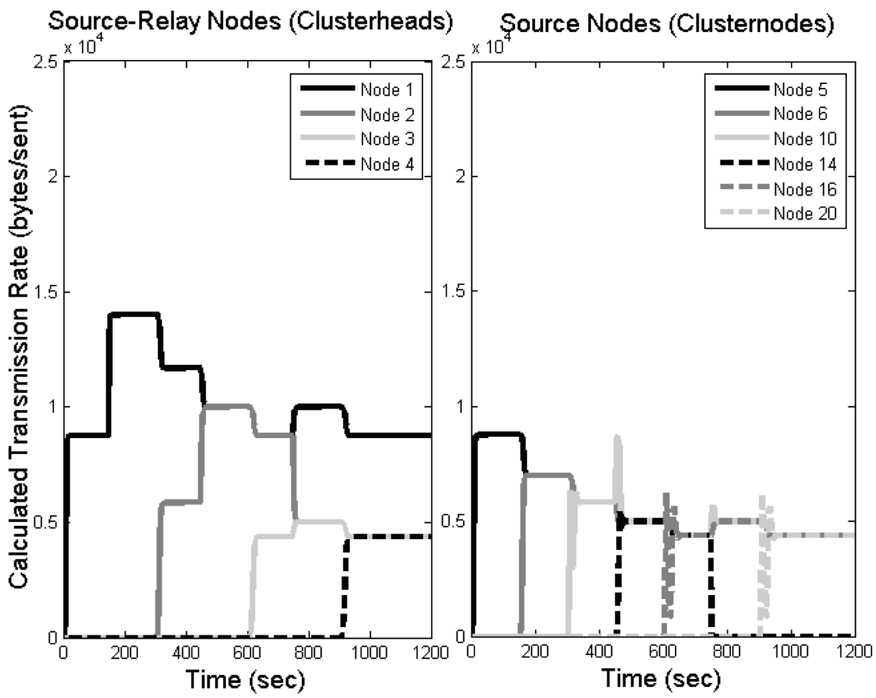


Figure 7. Calculated transmission rate (bytes sent per sec.) when α =1, β = 4, r =1.

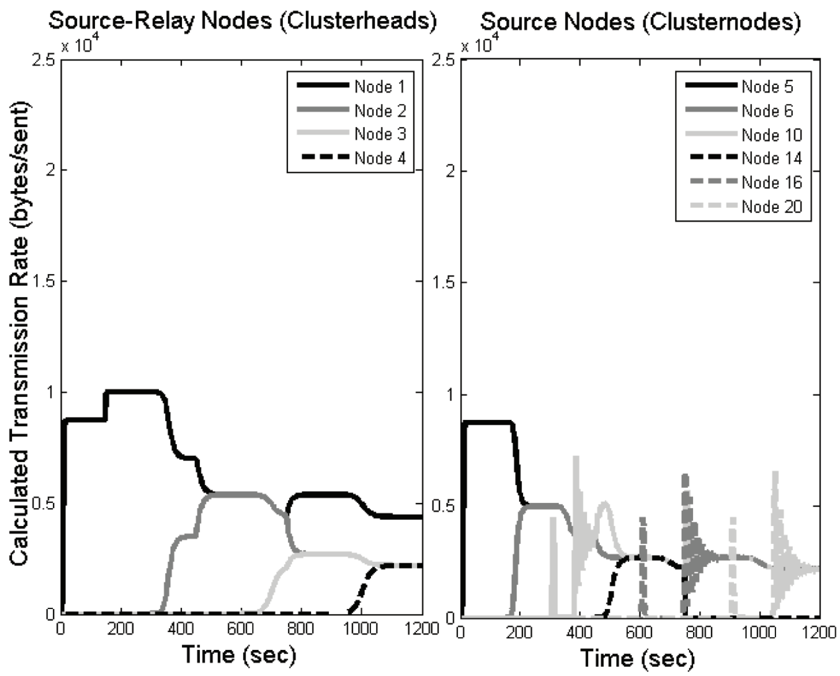


was able to re-converge to a new stable point after a change in network state (node activation). However, some fluctuations in calculated sending rates exhibited by flows initiated from nodes *10, 16* and *20*. This behavior is attributed to the fact that the buffers of nodes involved in the path between active nodes were highly loaded (since traffic flow rates were allowed to converge at high equilibrium values). Thus, with the activation of a new node, the increase of traffic injected into the network could not be smoothly accommodated by network's resources. Also, some fluctuations occurred when the flow of node *14* was deactivated. However, buffer overflows never occurred since the buffer overflow avoidance condition was satisfied. On the other hand, high traffic load injection into the network may lead to wireless channel capacity saturation, a phenomenon that was apparent in realistic network simulations.

When β increased to 4 (*Figure 7*) all flows became almost well-behaved while some very small fluctuations occurred after changes in the number of active nodes. Recall that the increase of β resulted in convergence of calculated rates at smaller equilibrium values x^*. As a result, the buffers within the network were not highly loaded. Hence, the increase of the traffic injected into the network was conveniently accommodated by network resources, while smooth converging behavior of the calculated transmission rates was preserved. Even though there is no analytical upper bound for β value, as β increases, the incoming traffic load can be conveniently accommodated but the quality of the received data at the sink may be reduced. It can be argued that the best setting for parameter β would be the lowest value that ensures stability and high calculated transmission rates at equilibrium (and thus, high quality), without causing wireless channel capacity saturation. The upper bound for β is further explored in realistic network scenarios.

The role of parameter α is discussed on the basis of *Figure 8*. In this scenario, parameters α and β were set to *3* and *4* respectively. Based on

Figure 8. Calculated transmission rate (bytes sent per sec.) when α =3, β=4, r=1



both buffer overflow avoidance and stability conditions, parameter α is lower bounded by *1* and upper bounded by β respectively ($1 < \alpha < \beta$). As can be seen, instability oscillations were observed at source nodes (*Figure 8*(b)) because the system was close to the stability limits. In addition, parameter α was found to be proportional to convergence time. Thus, fast convergence to the stable solution requires α to be close to *1* rather close to β (i.e. far from stability limits). This analytical finding is supported by *Figure 8* which illustrates the slow response of the system towards convergence when α was close β. On the other hand, low α values result in high calculated transmission rates at equilibrium that may not be accommodated by the underlying wireless medium. This issue (that cannot be efficiently simulated in matlab) as well as the influence of α on system performance were further investigated in realistic network scenarios.

In all the previous scenarios, the parameter *r* was set to *1*. Further matlab simulation studies were carried out in order to study the influence of *r* on stability. Recall that *r* was analytically found to be inversely proportional to convergence time, i.e. how fast or slow the system converges to the stable solution. Simulation results showed the value of *r* cannot grow unboundedly in order to achieve fast convergence. The value of *r* was tested across quite a large number of combinations of α and β values. Results showed that the calculated flow transmission rates were able to converge for every combination of α and β *w*hen $r \leq 2$.

Parameter Setting Based on NS2-based Realistic Network Scenarios

In this section, the impact of parameters α, β and *r* on a realistic network environment was investigated. A number of scenarios (shown in *Table 1*) were considered. The values of each parameter were chosen to be $4 \leq \beta \leq 7$, $1 \leq \alpha \leq 4$ (in order to satisfy the conditions of stability and buffer overflow avoidance), and $0.5 \leq r \leq 2$. Initially, parameter r was set to *1*.

Figure 9 illustrates the impact of α and β on packet delivery ratio (PDR) for the first scenario of operation involving *3* active nodes. It can be observed that the mean PDR for all active nodes was close to *1* (i.e. the sink received almost all packets sent from all active nodes) for the majority of β and α values. More specifically, for high values of β as for example $6 \leq \beta \leq 7$, high PDR was achieved for almost all values of α. Similarly, high PDR (close to *1*) was achieved for lower β values $5 \leq \beta \leq 6$ when $2 \leq \alpha \leq 4$, and for $4 \leq \beta \leq 5$ when $2 \leq \alpha \leq 3$. Realistic network simulation results validated control system type simulations. In particular, the decrease in PDR perceived for low values of α was mainly attributed to the increase in calculated transmission rates at equilibrium. Thus, the increase of traffic load injection into the network provoked wireless channel contention leading to packet loss. In addition, a sharp decrease in PDR was observed when the stability condition was threatened, as for example for $3.5 \leq \alpha \leq 4$ and $\beta = 4$.

Figure 10 shows the calculated transmission rates for the 3 active nodes for 3 combinations of parameter values. Table 2 refers to the validation of stability and buffer overflow avoidance conditions for scenarios of Figure 10.

As can be seen in Table 2, when $\alpha = 1$ and $\beta = 0.8$, neither stability nor buffer overflow avoidance conditions were satisfied. The violation of the first condition led to cycle instability in calculated transmission rates as shown in Figure

Figure 9. Packet Delivery Ratio for the first scenario of Table 1 involving 3 nodes (r=1)

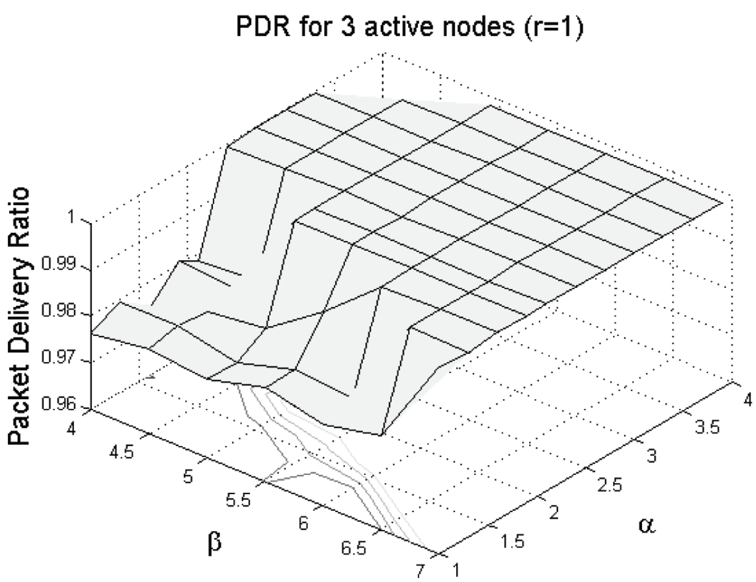


Table 2. Validation of stability and buffer overflow avoidance conditions for scenarios of Figure 10

α	β	$\beta > \alpha$	$\alpha\,[n\text{-}1] + \beta \geq n$	x^* (Kbytes/sec) when all active
1.0	0.8	X	$2.8 \not\geq 3$ X	–
0.25	0.5	✓	1>3 X	35
3.0	5.0	✓	11>3 ✓	3.18

10(a). In addition, due to the violation of the second condition, the summation of calculated transmission rates of all active nodes was greater than the buffer capacity of each node (35 Kbytes), thus leading to buffer overflows.

As illustrated in Figure 10 (b), when α =0.25 and β =0.5, the stability condition was satisfied whereas the buffer overflow avoidance condition was violated. Figure 10 (b) shows the calculated transmission rates after convergence, x^*, for each active node. As can be seen, the calculated transmission rate of each node is higher than or equal to *35* Kbytes/sec. However, nodes were not transmitting at such high rates but at the highest predefined transmission rate of *8* Kbytes/sec throughout the scenario duration. Even though the buffer capacities within the network could accommodate the generated traffic load, collisions at the wireless channel led to packet loss. As a result, the stream throughput for each active node measured at the sink was fluctuating as shown in Figure 11(a).

On the other hand, as shown in Figure 10 (c), when β =5 and α =3 none of the conditions were violated, while the calculated transmission rates were kept at lower values. Thus, each node was transmitting at the highest allowed predetermined transmission rate (see Figure 11 (b)) without causing packet loss.

It is worth pointing out that due to the low traffic load injected into the network in the presence of *3* active nodes, the mean end-to-end (EED) delay was kept below *4μsec*.

Figure 10. Calculated transmission rates for 3 active nodes scenario

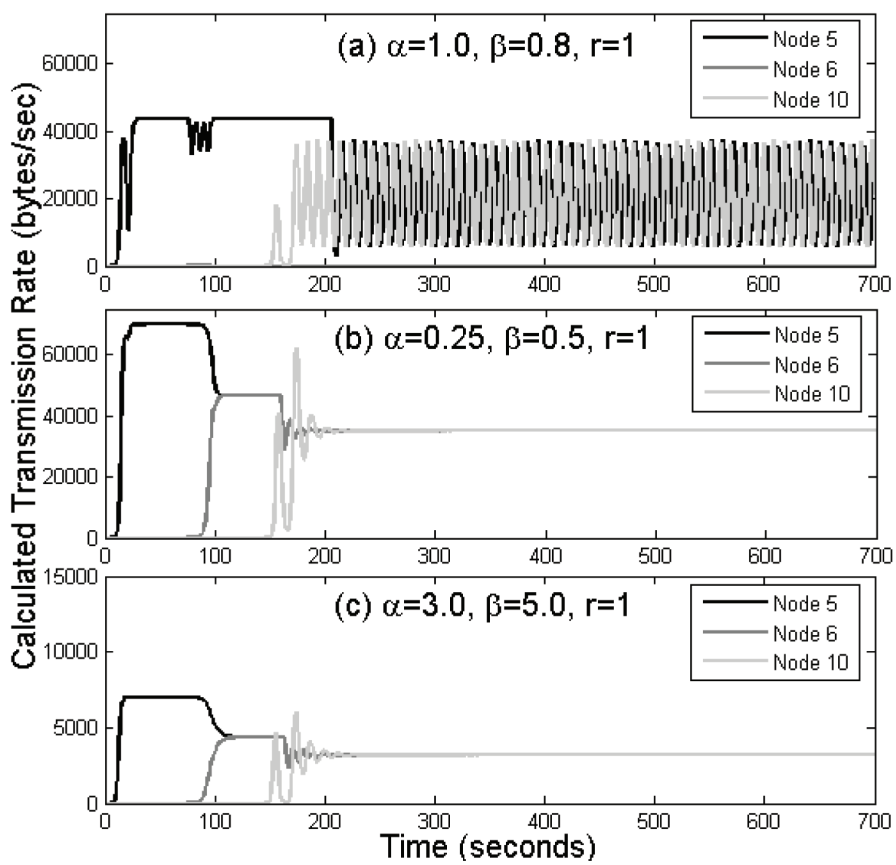


Figure 11. Stream throughput for 3 active nodes scenario measured at the sink

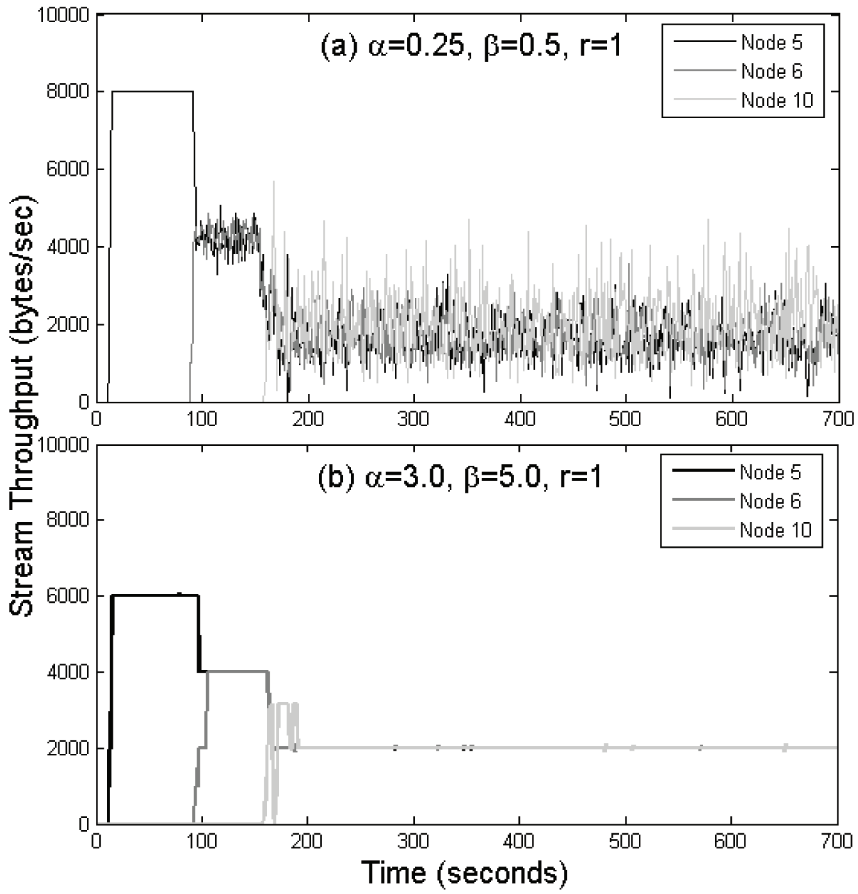


Figure 12 presents the PDR for the *4th* scenario involving *10* active nodes. The highest PDR for *10* active nodes (≈ 0.9) was obtained for $6 \leq \beta \leq 7$, and $1.8 \leq \alpha \leq 2.1$. *Figure 13* depicts the influence of parameters β and α on EED when *10* active nodes were involved. Low delay values ($\approx 10\,\mu sec$) were achieved when α was set between *1.8* and *2.1*, while β was ranging between *6* and *7*.

Analytical evaluations suggested that high values of r can contribute to fast convergence to the stable equilibrium solution. However, theoretical model analysis of complex scenarios in Matlab showed that network stability was achieved for $r \leq 2$. Increasingly, realistic network experiments in NS2 showed that for $r<1$ ($r=1$ in *Figure 14*),the calculated transmission rates of active nodes were not able to converge. On the other hand, convergence of calculated transmission rates was achieved for $r=1$. Extensive simulation results showed that the value of r must be kept less than or equal to *2* in order to preserve system stability for all combinations of α and β values, regardless of the number of active nodes.

Table 3 presents the combinations of α and β values that achieved the highest mean PDR for different number of active nodes. The parameter r was set to *1* in order to preserve smooth flow rate regulation. The last column of *Table 3* shows results obtained using *2* Mbps transmission rate at the MAC layer. It is worth pointing out that the results presented in this table consider only the scenarios where both the stability condition and

Figure 12. Packet Delivery Ratio for the fourth scenario of Table 1 involving 10 active nodes (r=1)

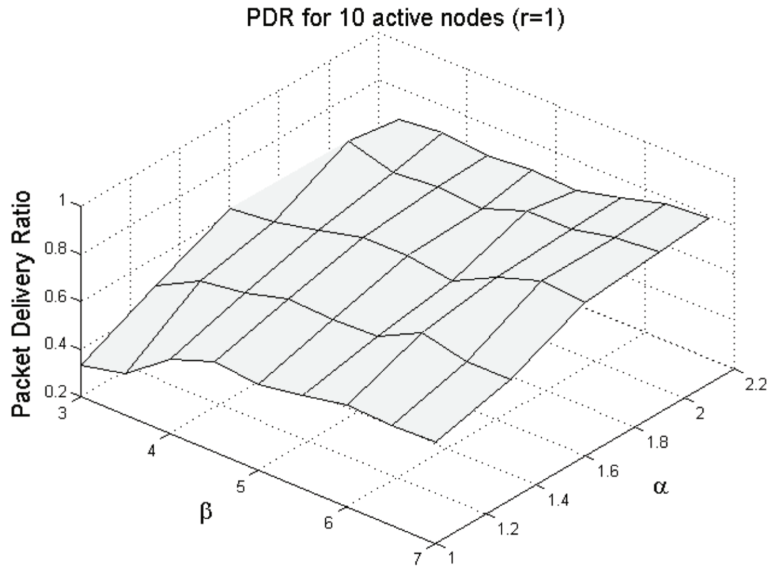
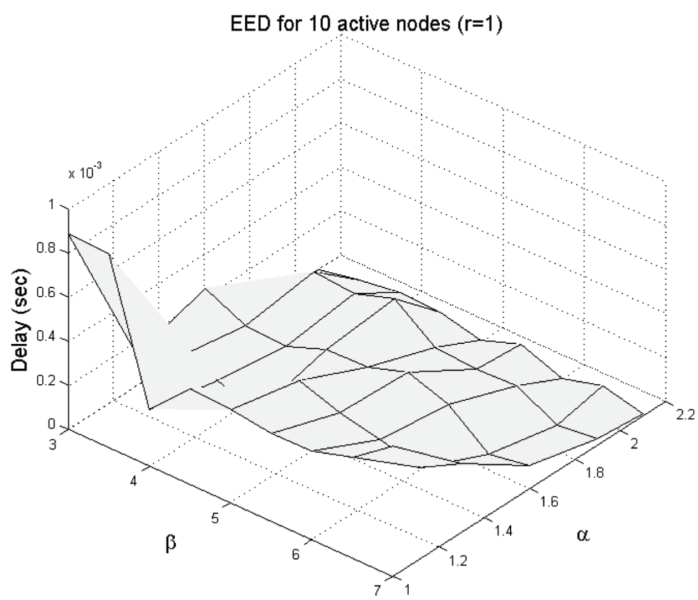


Figure 13. End-to-End Delay for the fourth scenario of Table 1 involving 10 active nodes (r=1)



the buffer overflow avoidance condition were satisfied.

Table 3 shows that in all scenarios, α values were significantly lower than β values. The values of α, that achieved the highest mean PDR in each scenario, ranged from *1.6* to *2.1*, while the values of β ranged from *3.3* to *7.0*. Results verified that as the number of active nodes scaled up, stable response of traffic flows and high mean PDR were achieved with the increase of both parameters (i.e. with the decrease of traffic flow transmission rates).

Figure 14. Calculated transmission rates for 5 active nodes scenario when r=0.5 and r=1

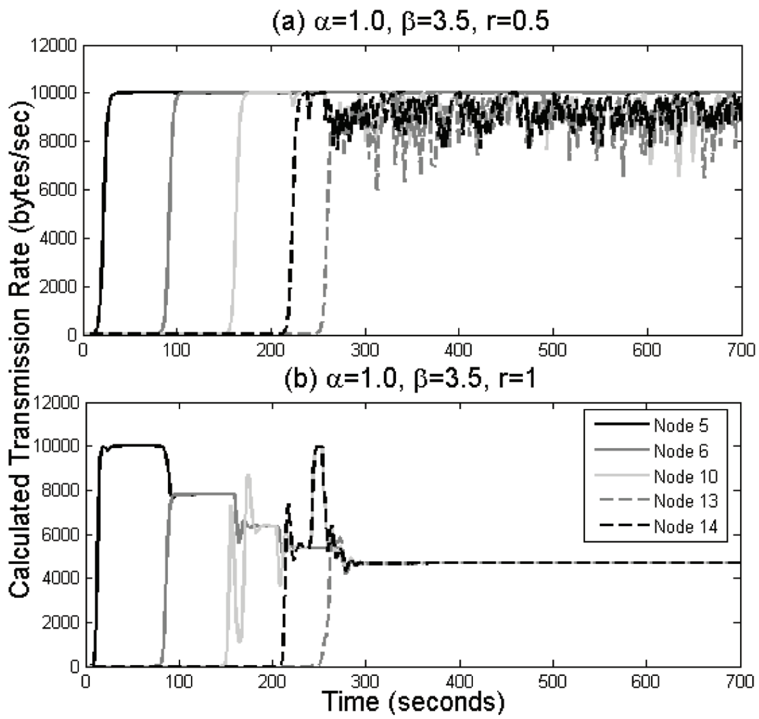


Table 3. Performance evaluations for realistic network conditions using NS2

α	*β*	No. of active nodes	Mean Packet Delivery Ratio	
			1 Mbps	2 Mbps
1.6	3.3	3	0.981	0.999
1.6	4.3	5	0.993	0.999
1.9	6.5	7	0.961	0.986
2.1	7.0	10	0.892	0.951

In addition, the mean PDR decreased slightly with the increase in the number of active nodes. The decrease of PDR was attributed to the inadequacy of network resources (e.g. wireless channel capacity) to accommodate the traffic load injected from a large number of active nodes. When the MAC transmission rate increased to *2* Mbps, higher PDR values were observed (last column of *Table 3*) as a result of the enhanced channel capacity.

It is beyond any doubt that the values of parameters α, β and r should be chosen to ensure stability of traffic lows as well as buffer overflow avoidance. The parameter r can be set equal to *1* in order to preserve convergence to equilibria as well as smooth flow rate regulation. Based on the evaluation results, the values of parameters α and β depend on the number of active nodes within the network. Therefore, both parameters should be adapted by each sending node according to the number of active nodes as follows:

$$a = \begin{cases} 1.6, & 1 \leq n \leq 5; \\ 2.1, & 6 \leq n \leq 10. \end{cases}$$
$$\beta = \begin{cases} 4.3 & 1 \leq n \leq 5; \\ 7.0 & 6 \leq n \leq 10. \end{cases} \tag{9}$$

The sink node is aware of the total number of active nodes within the network. The sink node can piggyback this number on control packets that are periodically broadcasted within the network. Each node can further spread this information out over the network by means of control packets.

Scalability and Fairness

Taking into consideration all the results presented thus far, the system proved to be adaptable against changing traffic load and achieved scalability by sharing buffer capacity of nodes to their active upstream nodes. For example in *Figure 7*, in the presence of one sender (node *5*) the stable equilibrium point of the system given by Equation 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 Equation 7 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.

Comparative Evaluations

The proposed LVCC approach was compared with the traditional AIMD rate adaptation mechanism which is currently involved in recent congestion control protocols for WSNs (Wan, 2003), (Rangwala, 2006), (Woo, 2001) and (Popa, 2006). The values of α, β and r were set to *2.4, 7* and *1* respectively, while scenarios *1* and *3* were considered, involving *3* and *5* active nodes respectively.

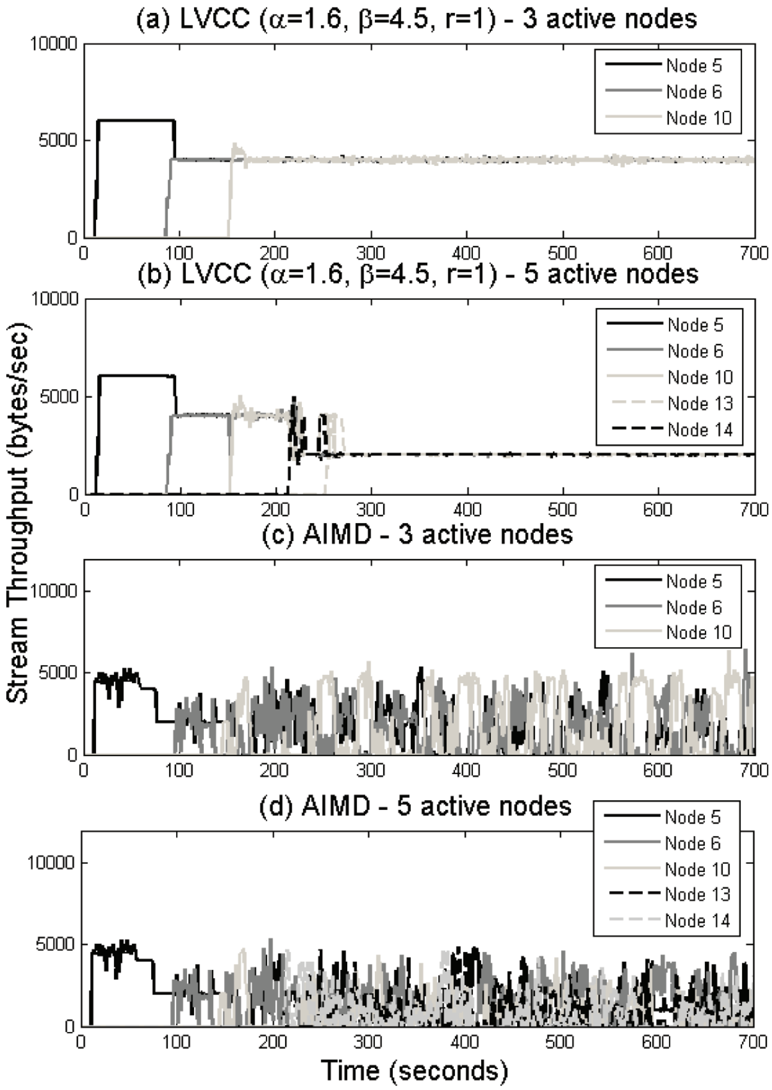
As shown in *Figure 15*(a) and (b), the proposed LVCC approach achieved smooth throughput for each active node while maintaining friendliness among competing flows. This controlled behavior is attributed to the powerful LV-based calculated transmission rate evaluation which effectively and efficiently perceives the available network bandwidth, and fairly shares it among active nodes.

On the other hand, as can be seen in *Figure 15*(c) and (d), the AIMD approach displayed a saw-tooth behavior which represents the probe for available bandwidth. The oscillations shown in *Figure 15*(c) and (d) were attributed to multiplicative rate decrease after packet loss events. Therefore, the AIMD rate control policy seems to be ineffective in wireless environments due to the frequent occurrence of packet loss events. In addition, AIMD seems inefficient for streaming applications since the saw-tooth rate behavior may violate the QoS requirements of a stream and can lead to significant variation in streaming media quality. Furthermore, the end-to-end nature of the AIMD mechanism makes it incapable of operating in error-prone wireless multihop networks and results in reduced responsiveness, increased latency and high error rates, especially during long periods of congestion. Contrarily, the LVCC approach operates in a hop-by-hop manner providing fast responsiveness to changing network conditions.

FUTURE RESEARCH DIRECTIONS

Recent technological advancements in low-cost small-scale imaging sensors, CMOS cameras and microphones have fuelled the emergence of novel multimedia applications over WSNs. The so-called Wireless Multimedia Sensor Networks

Figure 15. Throughput comparative evaluations between LVCC and AIMD for 3 and 5 active nodes



(WMSNs) have drawn the immediate attention of the research community (Akyildiz, 2007) and are expected to boost the capabilities of current wireless sensor networks. WMSNs applications e.g. multimedia surveillance networks, target tracking, environmental monitoring, and traffic management systems, require efficient gathering and transmission of multimedia data in the form of multimedia such as audio, image, and video. Under these circumstances, WMSNs introduce several research challenges for energy-efficient multimedia processing and communication, primarily related to the delivery of high quality of service (QoS).

In the near future, we can expect to see various applications based on multimedia wireless networks, where many types of sensors such as cameras, audio sensors, vibration sensors, and light sensors will be integrated in the same sensor node. In addition, it is expected that the number of such highly capable sensor nodes in multimedia applications will scale to tenths, hundreds or even thousands (Soro, 2009). Therefore, future protocols designed for WMSNs should be directed toward finding ways to preserve desirable characteristics such as network self-adaptation, scalability and fairness among competing traffic flows, while at the same time coping with the resource-constrained nature of the underlying network as well as the time and bandwidth requirements posed by applications.

This chapter proposes a novel bio-inspired congestion control approach (LVCC) targeting streaming applications in wireless sensor networks. The proposed approach was designed to exhibit the aforementioned characteristics. However, due to the application-dependent nature of WSNs, wireless sensor networks deployed for different applications may require different congestion control approaches. In addition to the challenges for reliable data transport in WSN (e.g. packet loss, delay), there exist additional challenges due to the unique requirements of the multimedia traffic, such as bounded delay and delay variation as well as minimum bandwidth demand. Therefore, a possible area of future work is to assign different priority classes to different kind of flows or different applications, which can be treated in a differentiated way by the congestion control algorithm.

CONCLUSION

This study investigates how a certain biologically inspired model can be employed to prevent congestion in small-scale multimedia WSNs. Inspiration from biological processes was drawn where global properties e.g., self-adaptation, stability, scalability and fairness 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 proposed, which aims at controlling the traffic flow rate at each sending node. Analytical evaluations and simulations were performed to understand how the variations of the model's parameters influence stability, sensitivity to parameters, scalability and fairness. Control system type simulations in Matlab validated the correctness of analytical results of Antoniou (2007) for plausible scenarios that could not be formally tested and showed that the proposed model achieves stability and smooth network operation under the analytically proposed conditions. Realistic scenarios of network operation and conditions were also taken into consideration for effective parameter setting. Realistic scenarios evaluation suggested certain values for parameters α,β and r that are able to achieve high packet delivery ratio, low end-to-end delay, scalability and fairness among competing flows. Furthermore, the proposed approach was found to outperform AIMD-like rate-based congestion control approaches for WSNs in terms of stability and flow rate smoothness. For future work, it is planned to investigate if and under what conditions parameter values can be analytically optimized using conventional or nature-inspired optimization techniques. In addition, the LVCC approach can be modified to cope with a set of different priority classes (e.g. by means of unequal traffic rates) corresponding to different kind of traffic flows.

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