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Improving hybrid ad hoc networks: The election of gateways

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ABSTRACT

The selection of an appropriate and stable route that enables suitable load balancing of Internet gateways is an important issue in hybrid mobile ad hoc networks. The variables employed to perform routing must ensure that no harm is caused that might degrade other network performance metrics such as delay and packet loss. Moreover, the effect of such routing must remain affordable, such as low losses or extra signaling messages. This paper proposes a new method, Steady Load Balancing Gateway Election, based on a fuzzy logic system to achieve this objective. The fuzzy system infers a new routing metric named *cost* that considers several networks performance variables to select the best gateway. To solve the problem of defining the fuzzy sets, they are optimized by a genetic algorithm whose fitness function also employs fuzzy logic and is designed with four network performance metrics. The promising results confirm that ad hoc networks are characterized by great uncertainty, so that the use of Computational Intelligence methods such as fuzzy logic or genetic algorithms is highly recommended.

1. Introduction

Mobile Ad hoc Networks (MANET) is a main interest area in ad hoc technologies that tries to deal with new trends in wireless communications. MANETs can reduce the impact of problems like deployment and maintenance costs of conventional wireless networks whereas they need more complex link management and routing. MANETs are composed of heterogeneous nodes that move in a confined space without a central infrastructure. Those nodes are interconnected through a multi-hop scheme that usually relies on routing protocols such as AODV or OLSR. Nevertheless, in current personal communications, the main interest of the users in a MANET is to find a reliable means of accessing the Internet through the available gateways in the network. Thus, those MANETs that have active connections to a public network are part of a type of ad hoc network called a hybrid MANET (H-MANET). In addition, the minimal infrastructure needed by MANET networks and their accessibility and adaptability [1] make them suitable to address the new scenarios for mobile communications.

In H-MANETs, the number of active gateways can vary, and they can be placed everywhere. Therefore, due to the heterogeneity and movement of the nodes, some of those gateways might need to manage higher traffic rates than others; that would cause a faster depletion of their batteries [2]. Moreover, the overload in the radio interface would increase packet losses due to signal interference, and the selection of one path to a gateway from another could seriously affect packet delay. Both problems, losses and delay, could have a direct effect on the user experience. Therefore, it becomes necessary to use traffic-engineering techniques to handle the load balancing between different gateways and to achieve better performance and resource optimization of H-MANETs [3]. Moreover, the resulting paths must be as stable as possible to avoid unnecessary control traffic required to reconfigure the entire MANET.

Unfortunately, most ad hoc routing protocols do not implement any load-balancing techniques [4]. A review of the load-balancing techniques employed in MANET shows that minimum-hop routing protocols tend to designate most centralized nodes with a high number of paths. Thus, only a few nodes must bear most of the network throughput, which translates into an increase in congestion and other undesirable effects such as battery depletion, high delays and routing overload.

Furthermore, load balancing can be associated with two separate ideas: pure load balancing and multipath routing techniques. Multipath routing does not show a significant improvement in mobile wireless networks because the majority of paths between any origin and destination share a significant number of nodes [4]. Therefore, if one of those path nodes failed, there would be

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a high probability that most possible routes to the Internet would be affected.

The protocols used in ad hoc multipath networks that address the interconnection between them and the Internet usually employ different adaptations of the Neighbor Discovery Protocol (NDP) [5]. The interconnection is achieved by sending Modified Router Advertisement (MRA) messages [6], which are an adaptation of the Router Advertisement messages sent by NDP. There are three different techniques to send these messages: proactive, reactive and hybrid methods. The proactive method consists of sending MRA messages periodically to the entire network whereas in the reactive technique, a route is only established on demand. The hybrid method creates two zones within the network. One of those areas is the proactive zone, delimited by the TTL of the IP packets, whereas outside that zone, a hybrid method is employed.

Note that the optimization of only one metric, such as load balancing, to improve network performance is likely to cause degradation in other metrics that affect the efficiency of the network [7]. Therefore, it is important to employ a multi-objective technique that considers different parameters or metrics of the system under study to achieve an optimum global solution [8]. However, multi-objective optimization in ad hoc networks is complex to achieve because the information needed for it is not always available in one node, or the signaling cost required to inform every device is not affordable. Thus, ad hoc networks and, more specifically, MANETs, must address a high degree of uncertainty [9], which makes them suitable to employ Computational Intelligence (CI) techniques. Some of the main causes of the uncertainty in MANETs include the following:

- Mobility of the nodes that makes their position unpredictable. Furthermore, links between nodes change continuously, which implies route actualization and side effects of fluctuating latency or delays within communications.
- Device heterogeneity: ad hoc networks can be formed by a wide variety of devices with, for example, different transmission power, signal sensitivity and available energy.
- Topology control is difficult to achieve due to the intrinsic mobility of MANET and to the limited number of control packets that can be sent in ad hoc networks to avoid battery depletion of nodes [10].
- Obstacles, diffraction and fading of signals in indoor environments and weather conditions in outdoor communications [11].

Therefore, to cope with the problem of uncertainty in MANETs and achieve steady load balancing that does not degrade other network performance metrics, this paper presents a new distributed method for gateway election by mobile nodes based on CI techniques such as fuzzy logic and genetic algorithms. Thus, the proposed method, Steady Load Balancing Gateway Election (SLBGE), which represents our main contribution, selects the best path to the right gateway in a MANET, considering only network status and performance variables that can be obtained autonomously by each node. The cost of each route is inferred by Fuzzy Inference System (FIS) based on multiple optimization objectives and stored in the routing table of the node. The cost for each path is actualized periodically with MRA arrivals.

Due to the mathematical complexity of precisely defining the right fuzzy sets of the input variables of the fuzzy system, they have been processed through the Genetic Algorithm (GA) whose novel fitness function is also based on a FIS.

The remainder of the paper is structured as follows. Section 2 presents a review of the most important related work that addresses the gateway selection problem. The method presented in this paper is described in detail in Section 3, whereas Section 4 shows the results obtained through a comparison with other, similar algorithms. To conclude this paper, the conclusions and future work are presented in Section 5.

2. Related work

As was mentioned above, routing and path election in MANETs incorporate a high degree of uncertainty: wireless communications, movement, heterogeneity and power constraints. Thus, different CI techniques are applied to routing, clustering, energy management, security and load balancing. Of the many CI techniques applied to MANET management, fuzzy logic and genetic or swarm intelligence algorithms [12] such as Ant Colony Organization (ACO) are among those commonly used [13].

Some representative examples of routing algorithms based on fuzzy logic for MANETs appear in [14], in which the authors present a solution to increase the time to live of a route, and in Sun et al. [15], which proposes entropy-based stability QoS routing with a fuzzy priority scheduler for MANETs.

For optimization with GA, a study [7] presents a multi-objective routing algorithm whose inputs refer to node status (residual energy, signal strength of the incoming messages and queue status), whereas in [16], to guarantee the stability of the clusters, the optimization process aims to achieve appropriate load balancing.

The contribution of Di Caro et al. [17] deserves special attention due to its relevance in bio-inspired techniques applied to routing in MANETs. In this case, the authors employ an Ant Colony Optimization algorithm to calculate the best route between nodes, keeping obtained paths active as long as possible. Moreover, this routing algorithm implicitly performs load balancing. This approach utilizes a proactive technique for path discovery based on the propagation and special control packets or *ants*. Then, previously established routes are actualized in a proactive approach over fixed intervals, sending new ants.

Focusing now on load balancing, a significant number of articles on H-MANETs have recently been published that use information gathered from control messages such as MRA as presented in [18], in which the author introduced a load-balancing technique for ad hoc and mesh networks based on the Round Trip Time (RTT), queue length or the number of active traffic sources. For example, in [19], the authors present a mixed integer linear problem as a solution for load balancing that minimizes the load of every link to the Internet. Unfortunately, this method needs an enormous amount of information that makes it extremely difficult to implement and compare with other approaches. In Ahn et al. [20], the authors analyze the information carried by the MRA messages and the delay in message reception to obtain metrics to be employed in load balancing such as number of hops, load of the gateway, variance of the arrival interval of the proactive messages and any combination of these.

A variant of the previous Internet draft can be found in [18], in which a load index is calculated for each mobile node and is later broadcast to build all the routing tables.

Among other techniques, fuzzy logic is also used in load-balancing calculations for H-MANETs. In [21], the authors present a related hybrid technique that adjusts the TTL of the MRA messages by the distance between the mobile nodes and the number of the nodes that are simultaneously connected to the Internet. Thereafter, mobile nodes choose their Internet gateway by the number of hops between them. An improved version of the previous contribution can be found in [22], in which a new method is presented to obtain the maximum distance to send control messages to the gateway.

Genetic algorithms have widely employed in optimization problems in the field of MANETs because most of those problems lack exact solutions, or their complexity makes them unaffordable. Therefore, GAs have been used in multiple ways as seen in [23]. On the other hand, the main difficulty of employing genetic algorithms is to find a suitable fitness function. To cope with the high degree of variability in MANETs, which involve serious problems of uncertainty, fuzzy logic provides a solution yielding values that can be used to evaluate network performance accurately in the context of multiple objectives. Thus, for example, in [24] the authors used a fitness function that employs previous information about the metrics obtained from different algorithms for comparison purposes. The information gathered from those comparisons is then employed to determine a new fitness function to improve former algorithms. Furthermore, in [25], the authors present a routing method for ATM networks that uses a fuzzy rule-based system (FRBS) whose input variables are several performance metrics of a link. The result inferred by the FRBS is a new metric that unites the input metrics.

Thus, the proposed optimization process, based on a GA whose fitness function is a fuzzy system tries to solve the gateway election problem as a multi-objective technique. The reason on using this method instead other based on, for example in the Pareto's efficient solution, are the difficulties that can arise to find the right values for all the coefficients due to the inherent uncertainty of MANETs.

3. Steady load-balancing gateway election

Suppose that we have the scenario shown in Fig. 1, in which the mobile nodes that form the MANET network can use any of the four available gateways. Thus, the mobile node 7 (N7) must obtain the right answer to this question: *What is the best gateway to connect to?*

However, the responses to that question are not simple. The gateway election must consider different aspects. The first and most important matter is to avoid overloading any one gateway. Thus, as seen in Fig. 1, N7 should avoid the route to gateway 1 through N5 and through gateway 2 by N3 because those paths are overloaded. If that happens, the number of collisions in the radio interface will grow rapidly. Therefore, more packets will be lost and the volume of retransmissions and control traffic will be increased, which will cause an important throughput decrease.

Furthermore, other factors that must be considered are that packet delay must be kept constant and the number of losses in every path must be kept low. Therefore, in our example, N7 would chose gateway 3 through N8 because, despite the hop count being three, the path seems to be less loaded.

As seen with the example depicted in Fig. 1, selection of a gateway is a complex problem. The solution provided in this paper considers different features of network performance. To cope with this issue, we propose a multi-objective method that optimizes four elements: delay, losses, load balancing and control packet overload.

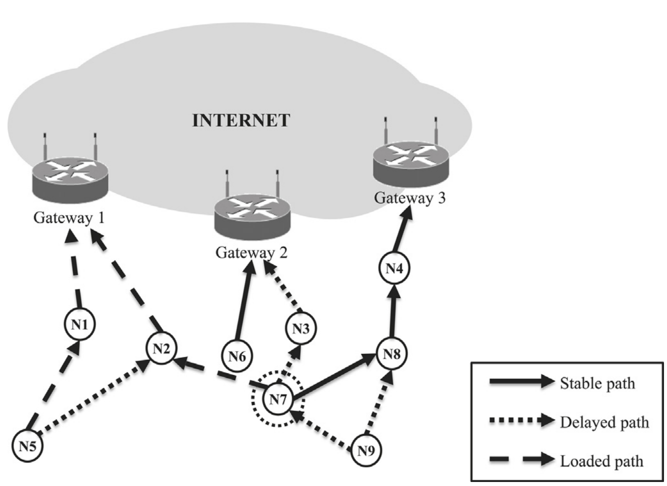

Fig. 1. MANET example.

The first three are linked to the stability of the paths to the Internet, whereas the last one considers the waste of resources in the mobile device due to the increase in consumption of data bandwidth by control packets.

These four features cannot be obtained through common standard protocols used in ad hoc networks. However, they employ a set of variables that can be derived from those features without increasing signaling traffic in the network. The variables that will be used in the present approach are the following:

- *MRA packet arrival variance (MAV)*: This variable is the variance of the difference between two MRA arrivals. Thus it is related to the delay of the packets. If the value is low, connectivity with the gateway will be high due to the periodic arrival of the MRA messages; therefore, it can be supposed that data packets will arrive faster to the gateway. These control messages must include the load of the gateway [20].
- *Control packet ratio (CPR)* [26]: CPR is the quotient of the error packets (EP) divided by the signaling packets (SP) sent. When the CPR is high, paths will be very stable and proactive processes are not necessary because paths will not break down; therefore, the loss ratio and the overload in the network also will be low. Thus, the CPR can be defined as follows:

$$CPR = 1 - \frac{EP}{EP + SP} \tag{1}$$

  As seen in Eq. (1), if there are any losses, the value of EP will be greater than zero; therefore, the number of signaling packets will increase, consequently reducing the value of CPR.
- *Load of the gateway (LG)*: This metric is defined in [27] as a fraction of the load that a gateway can manage. Evidently, a low value of this metric suggests that a particular gateway is underused.

The reason for employing only these variables in the present approach is that they are closely related to network performance. Moreover, by minimizing the number of variables, we avoid introducing any additional disadvantages related to the constraining features of ad hoc networks, such as battery lifetime.

The variables enumerated above will be the inputs to a Mamdani [28] fuzzy system. The Mamdani method is employed because it allows a more intuitive and human-like manner of translating expert knowledge [29]. This fuzzy system is located in every mobile node to obtain the cost associated with the route to the destination gateway. This system is named as FIS-C, and its process of calculating the cost for the path to each gateway is depicted in Fig. 2.

Whenever a MRA packet arrives at one node from a gateway, the values of the input variables of FIS-C are calculated and normalized to obtain a new inferred cost for the destination gateway. This new cost will be stored in the routing table in the correct row. An example of how a routing table [30] can be filled in after the reception of several MRA messages is shown in Table 1.

Despite Table 1 showing several routes to the Internet, each represented by a gateway, an outgoing message will only use the one whose cost is the lowest and only if that path remains active. When a route that is being used fails, it will be deleted from the default internet route and will be replaced with the route whose cost is the lowest among the remaining entrances. Moreover, if a mobile node

Table 1
Example of routing table.

Destination address	Next Hop address	Cost
Fixed node	Default_Internet_Route	0.2
Default_internet_route	Gateway_3	0.2
Gateway_1	N2	0.6
Gateway_2	N3	0.4
Gateway_3	N8	0.2

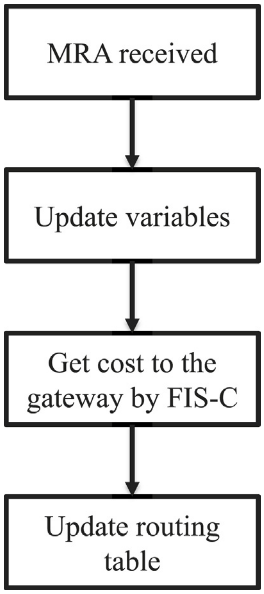

Fig. 2. Calculus process of the cost of the path to a gateway.

has several gateways from which to choose, it will select the one that received a lower output cost from the fuzzy system.

Each variable will be defined by three triangular fuzzy sets, such as those presented in Fig. 3, due to their efficiency and minimal computational complexity as stated in [31]. The number of fuzzy sets for each variable was established as three because tests made with more fuzzy sets did not improve the obtained results sufficiently to justify their complexity.

The three values shown in Fig. 3, X_{inf}, X_m and X_{sup}, for each one of the three input variables, will form the chromosomes of any individual of a genetic algorithm to get the best values that suits for a particular scenario. The reason to use the genetic algorithm in this type of problem is that it can achieve an optimal solution in a complex search space in which local solutions are abundant. The optimization process will be elaborated in the next section.

The fuzzy sets of the output variable of the fuzzy system implemented in every mobile device are shown in Fig. 4.

The rule base was designed to incorporate a hierarchical dependency between the three input variables and their effect on output cost. Therefore, the MAV variable, which is considered the most important of the three, ensures that the path to the gateway is not overloaded and that the election of that route is appropriate. The second variable in the precedence order is the CPR. Thus, higher CPR values indicate that many routes have been lost, which

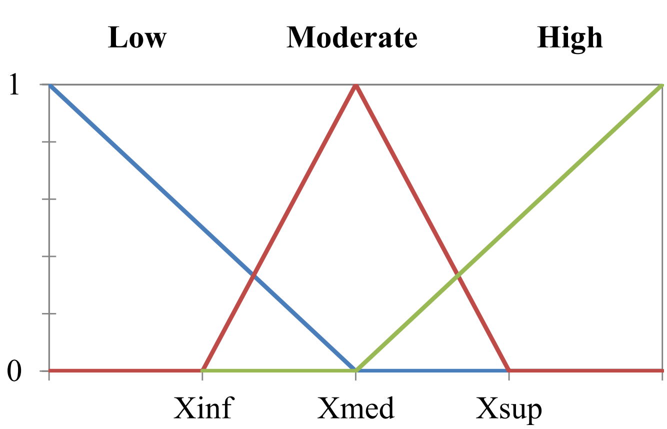

Fig. 3. Fuzzy set layout for each input variable of FIS-C.

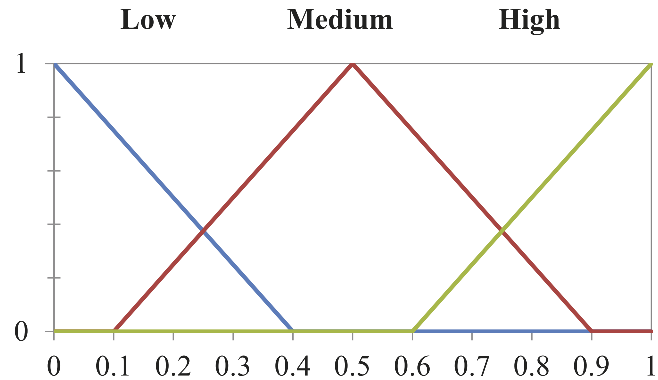

Fig. 4. Fuzzy sets of the *Cost* variable.

consequently implies more changes in destination gateways and an important decrease in network performance. Then, if the value of the third variable LG is high, that gateway must be temporarily avoided when accessing the Internet because it is overloaded. With these guidelines, the rule base is detailed in Table 2.

The next section addresses the optimization process of the fuzzy sets to adjust the performance of the system due to the intrinsic complexity of tuning those values a priori.

3.1. Optimization process

As has been commented above, the difficulties that surround the design of the fuzzy sets for FIS-C was faced by a classical optimization process based on a genetic algorithm. Therefore, the objective of the GA is to get the optimal values for X_{inf}, X_m and X_{sup} of each one of the input variables of FIS-C for a MANET Internet system. Then, these optimal values should obtain an improvement in the network performance.

The parameters X_{inf}, X_m and X_{sup} for each one of the inputs variables of FIS-C: MAV, CPR and LG, are the chromosomes of each one of the individuals of the population of the GA. These chromosomes have been named as follows:

- Variable MAV (MRA packet Arrival Variance): MAV_{inf}, MAV_{med} and MAV_{sup},
- Variable CPR (Control Packet Ratio): CPR_{inf}, CPR_{med} and CPR_{sup},
- Variable LG (Load of the Gateway): LG_{inf}, LG_{med} and LG_{sup}.

The whole optimization process based on a GA is depicted in Fig. 5 and is summarized as follows:

Table 2
Fuzzy rules of the FIS in each node to obtain the path cost to the gateway.

MAV	CPR	LG	Cost
L	L	L	L
L	L	M	L
L	M	L	M
L	M	M	L
L	M	H	M
L	H	L	M
L	H	M	M
L	H	H	M
M	L	L	L
M	L	H	M
M	M	M	M
M	H	H	M
H	L	L	M
H	M	M	H
H	M	H	H
H	H	H	H

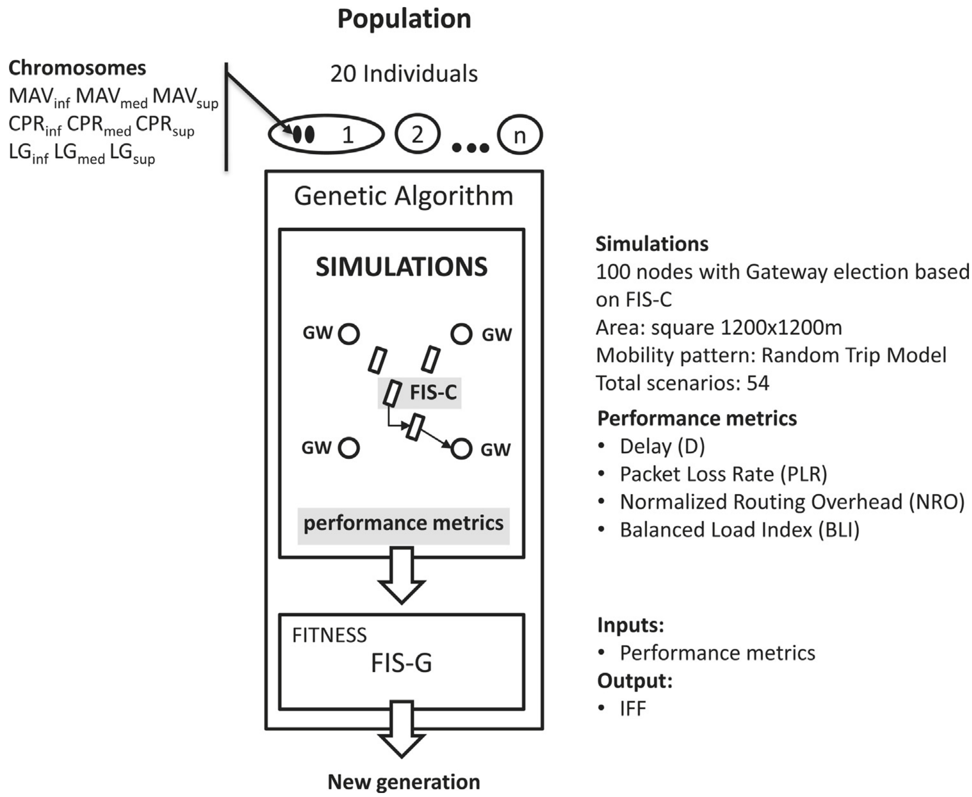

Fig. 5. Optimization process.

1. A random algorithm (described in Section 3.1.1) generates the values for the chromosomes of each of the individuals of the population.
2. For each one of the individuals, we calculate four performance metrics: delay, packet loss rate (PLR), normalized routing overhead (NRO) and balanced load index (BLI), through a set of simulations described in Section 3.1.2. The exact formulation of the performance metrics appears in Section 3.1.3.
3. Those performance parameters are the inputs of the fitness function of the GA that is implemented by a Mamdani fuzzy system, named FIS-G (detailed in Section 3.1.3). Then, for each one of the individuals is inferred a value that gives information about the whole network performance.
4. New generations are obtained by the classic genetic algorithm method that is shown in Section 3.1.4.

The whole process is repeated a predefined number of times to avoid over-fitting (this term will be explained in Section 4). After the optimization process ends, the values of MAV_{inf}, MAV_{med}, MAV_{sup}, CPR_{inf}, CPR_{med}, CPR_{sup}, LG_{inf}, LG_{med} and LG_{sup} can be applied to the fuzzy sets on FIS-C in every node of a MANET to achieve a steady load-balancing gateway election.

The following sections describe in detail each one of the phases enumerated above.

3.1.1. Chromosome initialization algorithm

A random process calculates the initial values of each chromosome for an individual. That process generates X_{inf}, X_m and X_{sup} for each variable jointly. The algorithm has four simple steps:

- *Step 1*: obtain a random value from zero to one for X_{inf}. If X_{inf} is over one, repeat step 1.
- *Step 2*: obtain a new random value (from 0 to 1) and add it to X_{inf} to get X_m. If X_m is over one, go to Step 1 and re-start the process.
- *Step 3*: obtain a new random value (from 0 to 1) and add it to X_m to get X_{sup}. If X_{sup} is over one, go to Step 1 and re-start the process.
- *Final step*: set to zero the initial point of the lower fuzzy set and set to one the right edge value of the higher fuzzy set.

3.1.2. Simulations

As was mentioned above, the fuzzy sets of the FIS-C that infers the cost of the routes to the Internet are optimized with a GA. The fitness function of that GA is also another fuzzy system, FIS-G. First, to obtain the performance metrics needed for the fitness function of the GA a set of simulations are executed for every descendant in each generation. Therefore, it is necessary to define a precise network model to generate different scenarios for the simulations.

The layout of the network topology that was employed to optimize the variables was a square area with an Internet gateway in every corner. Due to the obvious difficulties in modeling this type of experiment, it was simulated on the ns2 platform [32]. The main parameters and features of the proposed network are shown in Table 3.

From Table 3, note that the main advantage for our study of the mobility pattern used, namely, the Random Trip Model [33], is that the initial location and the speed of the nodes follow the final (steady) statistical distribution. Thus, the problems related to transients are avoided, whereas simulation techniques such as a warm-up simulation period are not required.

As shown in Table 4, the simulations use three different layouts based on the Random Trip Model (Node Mobility), in which the nodes are placed randomly within the map coordinates (three seeds) and move at three different speeds with two different transmission rates.

Therefore, for each one of the iterations of the genetic algorithm 54 different scenarios were simulated for every individual of the initial population to get the four performance metrics needed by

Table 3
Simulation parameters.

Transmission range	250 m
Ad hoc Protocol	Modified AODV [30]
Link layer	Local repair disabled
	Link layer detection enabled
	802.11b RTS/CTS enabled
Mobility pattern	Maximum speed: 2–10 m/s (interval = 1 m/s)
	Pause time: 10 s
	Random trip model
Traffic source	10 sources of Variable Bit Rate (VBR) randomly located
	Packet length: 300 bytes
	Rate: 10–20 packets/s
	Activity rate of the source: 50%
Integration support	Global connectivity
Nodes	100
GW coordinates (*x*, *y*) in meters	(0,0)
	(1200,0)
	(0,1200)
	(1200,1200)
MRA interval time	5 s
Active route timeout	10 s
Simulation time	1000 s

the FIS-G fitness function: delay, PLR, NRO and BLI. The final value for each one of those input variables of FIS-G is the normalized average of the 54 values obtained for each one in every simulated scenario.

3.1.3. FIS-G fitness function

The evaluation of each individual will be accomplished by a Mamdani fuzzy system, FIS-G, whose output will be employed as the fitness function that will determine the goodness of each solution of the GA, as proposed. This fitness function is based on a multi-objective metric that considers the following four network performance metrics:

- *Delay*: Delay is the transit time of the packets from their origin to their destination. In [34], delays of approximately 300 ms allow voice calls without losing quality. Three times this value is considered too high and will be used as the upper limit for normalization purposes.
- *Packet Loss Rate (PLR)*: This metric is the quotient of lost packets divided by the sent-packet total. A PLR that reaches 10% of packets sent is considered too high a value; therefore, this value will be used as the highest value for normalization purposes.
- *Normalized Routing Overhead (NRO)*: NRO is the relationship between correctly received packets (without duplication) and total control packets in the networks. For NRO, 5 is considered a very high value and is established as the upper limit of the metric for normalization.
- *Balanced Load Index (BLI)*: This metric indicates the degree of overload suffered by each gateway. It is calculated as follows:

$$BLI = \sum \left| \frac{GW_i}{\sum GW_i} - \frac{1}{N_{GW}} \right| \tag{2}$$

where GW_i is the load supported for each gateway and N_{GW} is the total number of gateways to the Internet. This value will be null if all the gateways support the same load of information toward the Internet. This value is normalized between zero and one.

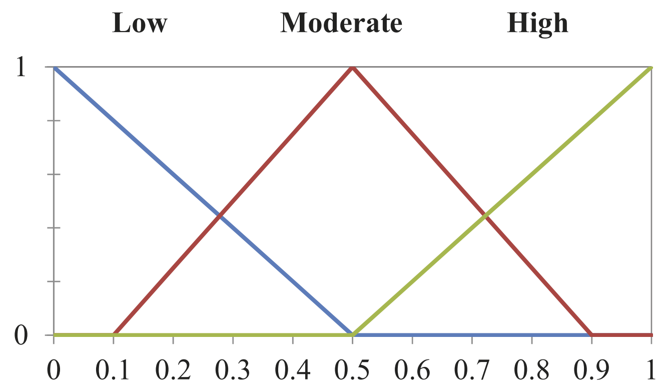

Fig. 6. Fuzzy sets defined for all of the inputs of FIS-G.

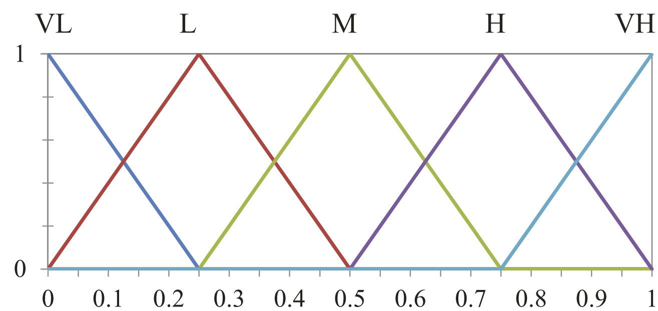

Fig. 7. Fuzzy set layout of the output variable of FIS-G.

Table 5
Excerpt from the rule base for the fitness function.

Delay	PLR	NRO	BLI	IFF
H	H	H	H	VH
M	M	M	M	M
L	L	L	L	VL

All the input variables of FIS-G: Delay, PLR, NRO and BLI will be defined with the same three triangular fuzzy sets such as the layout shown in Fig. 6.

The layout of the output variable of FIS-G is shown in Fig. 7, where a traditional model of five fuzzy sets is presented.

Table 5 presents an extract of the 81 rules that were employed. The whole rule base can be found in Amendment I. As shown, the output of the system will be low when the network is performing well. The optimal situation is when the delay, the PLR, the NRO and the BLI are low. The genetic algorithm minimizes the fitness function, as shown in Table 5, identifying as inappropriate output values those qualified as VH, whereas the best output values will be those categorized as VL. The output of FIS-G defines the fitness function, which was named as Improvement Performance Fitness Function (IFF).

The process of optimization will end when it obtains a good IFF value or when the maximum number of generations is completed.

Table 4
Number of simulation scenarios for the optimization process.

Node mobility		Seeds		Speeds		VBR Traffic		Total
3		10		2 m/s		10 packets/s		54 scenarios
	X	100	X	5 m/s	X	20 packets/s	=	
		1000		10 m/s				

Table 6
Genetic operators.

Operator	Type
Encoding	Real
Selection	Stochastic uniform
Crossover	Scattered
Mutation	Gaussian
Reproduction	Elite count

3.1.4. Offspring generation

Then, after the fitness evaluation process, the new individuals are compared with the previous generation. All individuals from both generations are ranked based on their fitness values. An individual with a small value of fitness is considered better than one with a large fitness value. The individuals with best results are retained in the population as successive generations evolve. There are two means of obtaining new individuals in a generation: crossover and mutation.

Crossovers are employed to create new individuals in the current population by combining and rearranging parts of the existing individuals. The idea behind the crossover is that it may result in an even better individual by combining the two fittest individuals. The crossover operator is implemented as a scattered function.

Conversely, in GA, mutations occasionally occur to allow a certain child to obtain features that are not possessed by either parent. This process helps a GA to explore new and better genetic material that was not considered previously. For this purpose, a Gaussian mutation function was utilized. The complete set of genetic operators is shown in Table 6.

4. Results

The final values obtained in the optimization process, which define the three points of the fuzzy set layout for the input variables of FIS-C, shown in Fig. 3, were selected from the best IFF obtained in the fitness process. These values are summarized in Table 7. We have simulated 30 different evolution tests with initial population of 20 individuals to obtain a fitness value. The stopping criterion

Table 7
Optimized value obtained for the fuzzy sets of one node.

	X_{inf}	X_{med}	X_{sup}
MAV	0.1388	0.3999	0.5207
CPR	0.3021	0.3418	0.5611
LG	0.1997	0.4610	0.9996

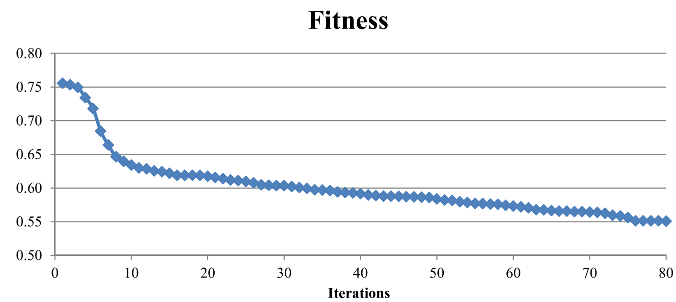

Fig. 8. Fitness evolution.

was established in 80 generations as shown in Fig. 8. The simulation was finalized at that point to avoid over-fitting.

Once the fuzzy sets of the FIS that infer the cost of a route to a gateway in every node are optimized, to check how the proposed SLBGE method performs, it is compared with other existing approaches. The methods have been chosen to check different approaches to the proposed problem:

- A widely used analytic approach (Ahn Proposal or AP) [20]. For our experiment, we used the product of the load and the variance.
- A fuzzy system that is similar to that proposed in this paper (Path Load Balanced-Fuzzy Logic or PLBFL) [21]
- AntHocNet [17], a solution that uses a different CI technique, Ant Colony Optimization.

These proposals were already summarized in Section 2.

Therefore, the metrics delay, PLR, BLI and NRO, as calculated in Section 3.1.2, will also be obtained following the proposals of the

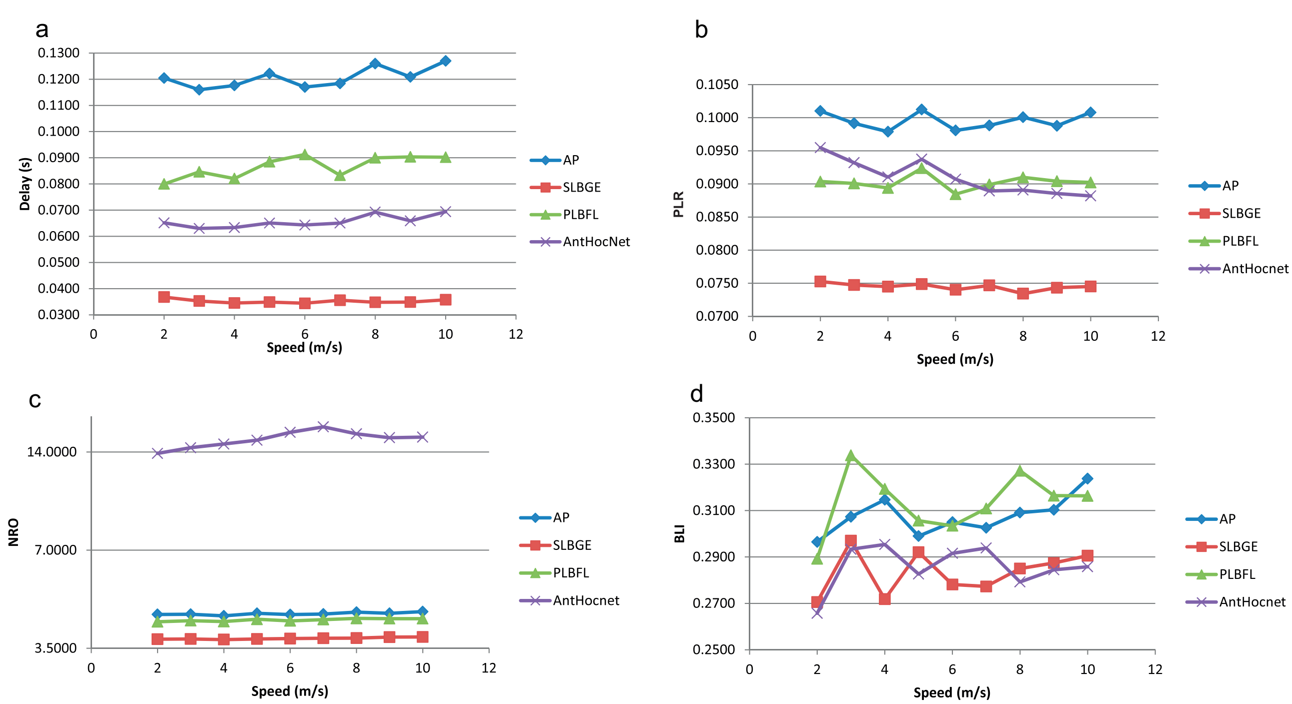

Fig. 9. Results for 10 packets/s: (a) results for the packet delay, (b) PLR results, (c) NRO results and (d) BLI result.

other authors. The simulations prepared to test the methods under comparison have been designed with two different data rates, a low data rate and a higher one, to check how each method adapts itself to load oscillations. Moreover, each point on the graphs was obtained for 10 different scenarios and three different seeds. The scenarios do not coincide with those employed in the optimization process to check how the proposed system can behave under different conditions. Nevertheless, the other values of the simulation were kept unchanged (see Table 5). The results obtained for delay, PLR, NRO and BLI are shown in Fig. 9.

As shown in Fig. 9, it is evident that the proposed method noticeably improves the value of packet delay compared with the other three alternatives. The greater delay for AP is due to its use of the load as the metric to select the gateway; the delay implies that the path selected is less loaded, but not necessarily the shortest path, and often yields routes with a higher hop count than other methods. AntHocNet improves considerably on the AP method because it uses a proactive technique based on ant messages, and this type of algorithm usually performs better than pure reactive ones at the expense of high control-packet overload. Both fuzzy methods (PLBFL and SLBGE) clearly improve on the AP algorithm because they use several variables to obtain routes to the Internet. Furthermore, SLBGE achieves an even better delay because it counts with a set of variables adapted to the behavior of the system of routes; hence, it finds more stable routes.

For PLR, the proportional differences between the methods are lower than the delay ones, but our approach achieves a significant decrease compared with the other results. The good results of SLBGE, as well as with the delay, occur because the obtained paths are very stable because the metrics employed allow for the discrimination of fallen links.

The first noticeable points in the NRO graph are the high values of overload for AntHocNet. This is due to its use of ants to keep as refreshed as possible all active paths to the Internet. The other three methods obtain lower values than AntHocNet. However, SLBGE stands out from among those because the paths obtained by it are

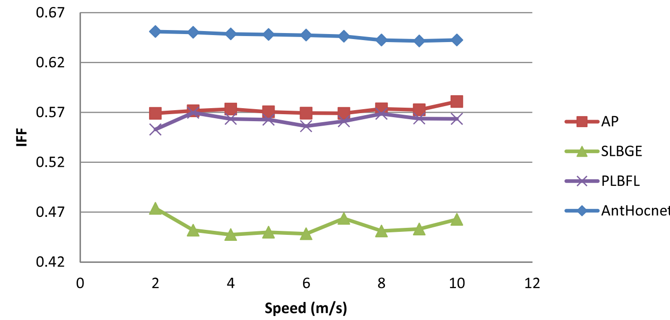

Fig. 10. IFF for 10 packet/s.

more stable and need less reactive processes to obtain new routes to the Internet; consequently, the overload is less.

Moreover, the load balancing curves depicted in Fig. 9 present a difference between our approach and AP and PLBFL and show that our approach is similar to AntHocNet; the overload in the network caused by the employed method is decreased.

To check how the IFF performs, Fig. 10 shows the values obtained for the four algorithms.

As shown, it is clear that the optimization process was appropriate because our approach, with the optimized fuzzy sets, performs much better than the other three methods because high values of one of the metrics penalize the result. Therefore, the IFF results for AntHocNet are the worst due to its high overload.

In summary, the results of the presented multi-objective gateway election system for the different metrics shown in the previous figures considerably improve the values obtained by the other techniques without negatively affecting the load-balancing features.

To complete the analysis of the comparison between the three methods, Fig. 11 shows the results obtained for the simulation scenario for 20 packets per second.

As shown, the obtained results maintain the previously mentioned differences, indicating that our approach performs better

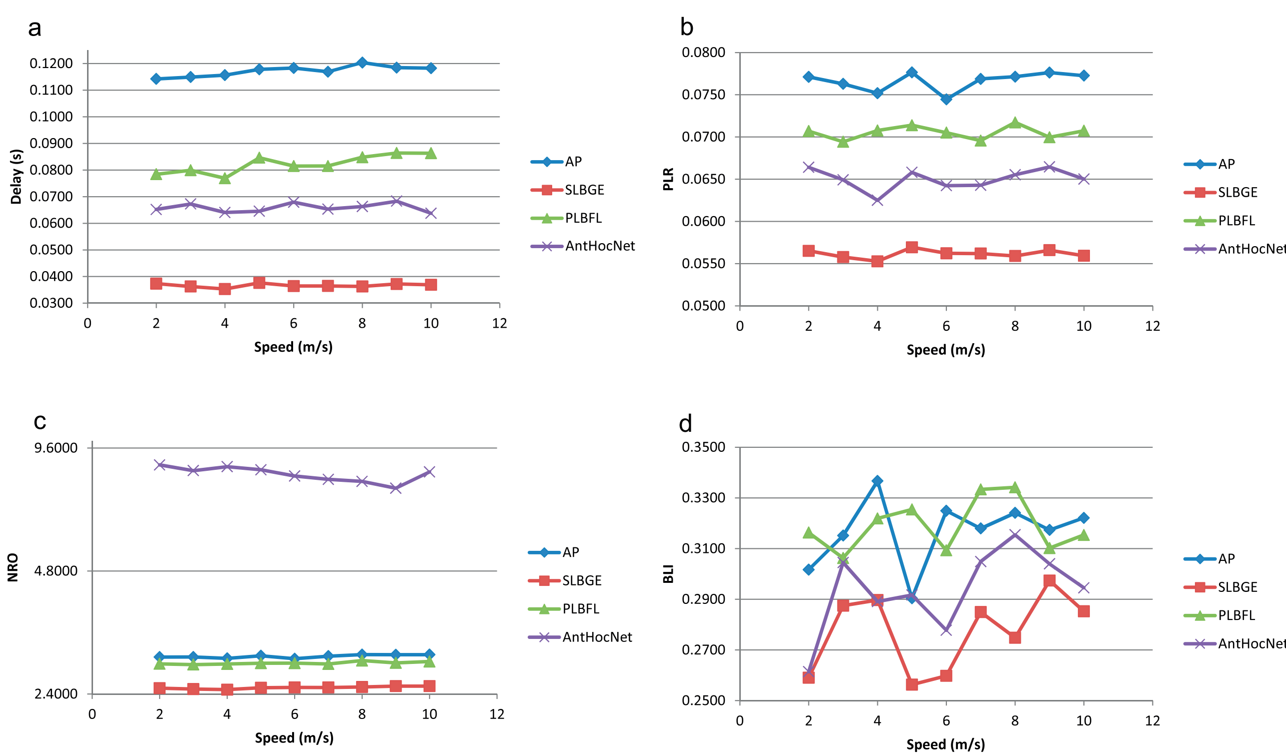

Fig. 11. Results for 20 packets/s: (a) results for the packet delay, (b) PLR results, (c) NRO results and (d) BLI result.

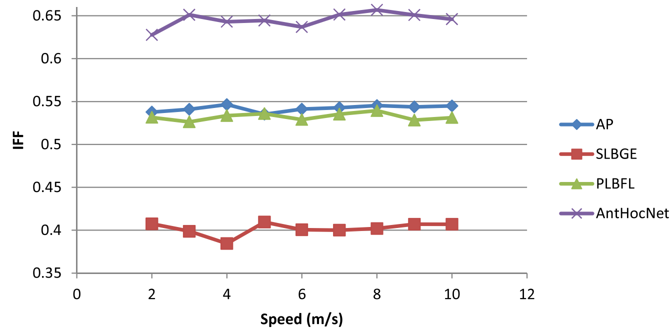

Fig. 12. IFF for 20 packet/s.

than the other three. When the load on the network increases, the results of the delay are similar. However, in the presence of packet losses, AntHocNet improves considerably compared with AP or PLBF. In the case of network overload, the difference between AntHocNet decreases, although it keeps showing high values; however, the IFF factor remains the worst, as shown in Fig. 12. Moreover, the proposed method keeps obtaining better results, even for load balancing, due to its stable paths.

The confidence levels of the results depicted in the figures in the present section are included in an amendment to this paper.

5. Conclusions and future work

The movement of the nodes that form an ad hoc network makes the measurement of most of their features completely unpredictable a priori. Thus, it is impossible to employ techniques based on analytic methods to improve their performance.

For that reason, techniques based on Computational Intelligence, despite its complexity, can be successfully applied to those processes that imply a significant degree of uncertainty, such as mobile ad hoc networks, achieving significant improvements in results.

This paper presents the first approach to a method for the election of a gateway in H-MANETs through a multi-objective optimization process that employs metrics obtained autonomously by individual nodes. The selection of the gateway is achieved by a FIS that calculates the cost of a path to the Internet based on variables that are closely related to network performance.

Another contribution of this paper is that the proposed fuzzy system is optimized by a genetic algorithm whose fitness function is also tuned by another fuzzy system. Thanks to that fitness function, a unique value can be used to compare the performance of the network obtained by other algorithms because the obtained paths are more stable due to the multi-objective optimized cost. Likewise, those paths that cause fewer route updates have a longer lifetime, hence delivering the best performance of all the metrics analyzed. Thus, the proposed fitness function FIS-G takes into account the metrics that can affect the gateway election problem but without the constraints of defining the exact value for a coefficient. Moreover, the flexibility of knowledge base definition allows a better tuning process giving response for the variability of the metrics under study in a MANET whose values effect in very different ways the performance of the system. Therefore, this multi-objective method can be adapted progressively to different environments modifying only some parts of the knowledge base of FIS-G.

Moreover, the experimental results considerably improve on those obtained by the other three presented algorithms currently proposed for ad hoc networks.

Now we are making new tests with the same optimized fuzzy sets in different scenarios to try to extend the obtained results and to check their effectiveness. These new tests are based on scalability (nodes and gateways) and they used different mobility models and dimensions of the boundaries of the network.

Future work can be aimed at achieving an effective learning process for the fuzzy rules that are employed in the system. Moreover, the inclusion of other input variables that model new network metrics could be studied to improve the performance of the entire system.

Acknowledgments

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Amendment I. Rule base of the FIS for the fitness function of the GA.

Table 8.

Table 8
Rule base for FIS-G.

Rule	Delay	PLR	NRO	BLI	IFF	Rule	Delay	PLR	NRO	BLI	IFF
1	L	L	L	L	VL	42	H	M	M	M	H
2	M	L	L	L	VL	43	L	H	M	M	M
3	H	L	L	L	L	44	M	H	M	M	H
4	L	M	L	L	VL	45	H	H	M	M	H
5	M	M	L	L	L	46	L	L	H	M	L
6	H	M	L	L	L	47	M	L	H	M	M
7	L	H	L	L	L	48	H	L	H	M	H
8	M	H	L	L	L	49	L	M	H	M	M
9	H	H	L	L	M	50	M	M	H	M	H
10	L	L	M	L	VL	51	H	M	H	M	H
11	M	L	M	L	L	52	L	H	H	M	H
12	H	L	M	L	L	53	M	H	H	M	H
13	L	M	M	L	L	54	H	H	H	M	VH
14	M	M	M	L	L	55	L	L	L	H	L
15	H	M	M	L	M	56	M	L	L	H	L
16	L	H	M	L	L	57	H	L	L	H	M
17	M	H	M	L	M	58	L	M	L	H	L
18	H	H	M	L	H	59	M	M	L	H	M
19	L	L	H	L	L	60	H	M	L	H	H
20	M	L	H	L	L	61	L	H	L	H	M
21	H	L	H	L	M	62	M	H	L	H	H
22	L	M	H	L	L	63	H	H	L	H	H
23	M	M	H	L	M	64	L	L	M	H	L
24	H	M	H	L	H	65	M	L	M	H	M
25	L	H	H	L	M	66	H	L	M	H	H
26	M	H	H	L	H	67	L	M	M	H	M
27	H	H	H	L	H	68	M	M	M	H	H
28	L	L	L	M	VL	69	H	M	M	H	H
29	M	L	L	M	L	70	L	H	M	H	H
30	H	L	L	M	L	71	M	H	M	H	H
31	L	M	L	M	L	72	H	H	M	H	VH
32	M	M	L	M	L	73	L	L	H	H	M
33	H	M	L	M	M	74	M	L	H	H	H
34	L	H	L	M	L	75	H	L	H	H	H
35	M	H	L	M	M	76	L	M	H	H	H
36	H	H	L	M	H	77	M	M	H	H	H
37	L	L	M	M	L	78	H	M	H	H	VH
38	M	L	M	M	L	79	L	H	H	H	H
39	H	L	M	M	M	80	M	H	H	H	VH
40	L	M	M	M	L	81	H	H	H	H	VH
41	M	M	M	M	M						

Amendment II. Confidence levels of the comparison results shown in Section 4.

Tables 9–24.

Table 9
Medium values obtained for delay at 10 packets/s.

Delay	AP	SLBGE	PLBFL	AntHocNet
2	0.1205	0.0368	0.0800	0.0651
3	0.1160	0.0353	0.0846	0.0630
4	0.1176	0.0345	0.0820	0.0633
5	0.1222	0.0349	0.0885	0.0651
6	0.1170	0.0344	0.0912	0.0643
7	0.1184	0.0356	0.0833	0.0650
8	0.1260	0.0348	0.0900	0.0692
9	0.1209	0.0349	0.0903	0.0659
10	0.1270	0.0358	0.0902	0.0694

Table 10
Confidence intervals for 95% of the delay at 10 packets/s.

Ap		SLBGE		PLBFL		AntHocNet	
min	max	min	max	min	max	min	max
0.1070	0.1340	0.03450	0.03903	0.0718	0.0882	0.0590	0.0713
0.1037	0.1282	0.03347	0.03705	0.0765	0.0927	0.0567	0.0693
0.1048	0.1304	0.03304	0.03598	0.0734	0.0907	0.0570	0.0697
0.1100	0.1344	0.03301	0.03672	0.0791	0.0978	0.0589	0.0713
0.1009	0.1331	0.03287	0.03595	0.0778	0.1046	0.0563	0.0723
0.1078	0.1290	0.03397	0.03717	0.0758	0.0908	0.0602	0.0699
0.1172	0.1348	0.03346	0.03611	0.0817	0.0983	0.0637	0.0748
0.1114	0.1304	0.03333	0.03641	0.0827	0.0979	0.0608	0.0710
0.1162	0.1377	0.03391	0.03760	0.0819	0.0986	0.0635	0.0753

Table 11
Medium values obtained for PLR at 10 packets/s.

PLR	AP	SLBGE	PLBFL	AntHocnet
2	0.1010	0.0753	0.0904	0.0955
3	0.0992	0.0747	0.0901	0.0932
4	0.0979	0.0745	0.0894	0.0910
5	0.1012	0.0749	0.0924	0.0937
6	0.0981	0.0740	0.0884	0.0907
7	0.0988	0.0747	0.0899	0.0889
8	0.1001	0.0734	0.0910	0.0891
9	0.0988	0.0743	0.0904	0.0885
10	0.1008	0.0745	0.0902	0.0882

Table 12
Confidence intervals for 95% of the PLR at 10 packets/s.

Ap		SLBGE		PLBFL		AntHocNet	
min	max	min	max	min	max	min	max
0.09727	0.10477	0.0726	0.0779	0.08702	0.09371	0.0920	0.0989
0.09553	0.10277	0.0720	0.0775	0.08695	0.09318	0.0899	0.0965
0.09493	0.10084	0.0721	0.0769	0.08654	0.09225	0.0882	0.0938
0.09807	0.10437	0.0724	0.0774	0.08941	0.09532	0.0908	0.0967
0.09532	0.10083	0.0718	0.0762	0.08568	0.09121	0.0881	0.0934
0.09628	0.10135	0.0724	0.0769	0.08755	0.09225	0.0866	0.0912
0.09746	0.10269	0.0714	0.0754	0.08842	0.09356	0.0866	0.0915
0.09583	0.10173	0.0721	0.0766	0.08804	0.09275	0.0839	0.0909
0.09790	0.10370	0.0723	0.0767	0.08728	0.09316	0.0846	0.0900

Table 13
Medium values obtained for NRO at 10 packets/s.

NRO	AP	SLBGE	PLBFL	AntHocnet
2	4.4453	3.7345	4.2237	13.8659
3	4.4524	3.7391	4.2548	14.4292
4	4.4021	3.7225	4.2291	14.8107
5	4.4816	3.7383	4.2972	15.2128
6	4.4428	3.7493	4.2482	16.0788
7	4.4594	3.7590	4.2864	16.7228
8	4.5172	3.7610	4.3248	15.9179
9	4.4828	3.7894	4.3148	15.4860
10	4.5341	3.7931	4.3150	15.5490

Table 14
Confidence intervals for 95% of the NRO at 10 packets/s.

Ap		SLBGE		PLBFL		AntHocNet	
min	max	min	max	min	max	min	max
4.3521	4.5384	3.6598	3.8092	3.7910	4.6564	13.1726	14.5592
4.3649	4.5399	3.6792	3.7989	3.8459	4.6637	13.2027	15.6556
4.3435	4.4606	3.6822	3.7627	3.7821	4.6761	13.6999	15.9216
4.4025	4.5607	3.6776	3.7991	3.8441	4.7504	13.7676	16.6580
4.3835	4.5021	3.6974	3.8013	3.6233	4.8731	14.4709	17.6866
4.3992	4.5196	3.7084	3.8096	3.8991	4.6737	15.3013	18.1442
4.4540	4.5805	3.7133	3.8088	3.9261	4.7236	14.7241	17.1118
4.4017	4.5639	3.7306	3.8481	3.9515	4.6781	14.4020	16.5701
4.4672	4.6010	3.7368	3.8494	3.9161	4.7139	14.3828	16.7151

Table 15
Medium values obtained for BLI at 10 packets/s.

BLI	AP	SLBGE	PLBFL	AntHocnet
2	0.2965	0.2706	0.2892	0.2657
3	0.3073	0.2970	0.3338	0.2933
4	0.3147	0.2718	0.3193	0.2954
5	0.2990	0.2921	0.3056	0.2826
6	0.3050	0.2781	0.3034	0.2916
7	0.3026	0.2773	0.3109	0.2939
8	0.3091	0.2850	0.3272	0.2792
9	0.3103	0.2874	0.3164	0.2845
10	0.3237	0.2906	0.3163	0.2858

Table 16
Confidence intervals for 95% of the BLI for 10 packets/s.

Ap		SLBGE		PLBFL		AntHocNet	
min	max	min	max	min	max	min	max
0.26195	0.33107	0.2299	0.3112	0.2534	0.3250	0.2365	0.2950
0.27388	0.34075	0.2629	0.3311	0.2919	0.3757	0.2625	0.3241
0.28027	0.34909	0.2328	0.3109	0.2874	0.3513	0.2614	0.3294
0.25145	0.34652	0.2426	0.3416	0.2483	0.3630	0.2374	0.3278
0.26570	0.34434	0.2412	0.3151	0.2695	0.3373	0.2537	0.3295
0.27026	0.33489	0.2440	0.3106	0.2805	0.3412	0.2630	0.3247
0.27303	0.34518	0.2494	0.3206	0.2922	0.3622	0.2485	0.3100
0.28055	0.34007	0.2560	0.3188	0.2811	0.3518	0.2560	0.3129
0.29331	0.35417	0.2570	0.3242	0.2792	0.3535	0.2529	0.3187

Table 17
Medium values obtained for delay at 20 packets/s.

Delay	AP	SLBGE	PLBFL	AntHocNet
2	0.1142	0.0373	0.0784	0.0652
3	0.1149	0.0363	0.0799	0.0673
4	0.1157	0.0353	0.0769	0.0641
5	0.1178	0.0376	0.0846	0.0645
6	0.1183	0.0364	0.0815	0.0679
7	0.1169	0.0365	0.0815	0.0653
8	0.1204	0.0363	0.0848	0.0663
9	0.1185	0.0372	0.0864	0.0683
10	0.1183	0.0369	0.0863	0.0638

Table 18
Confidence intervals for 95% of the delay at 20 packets/s.

Ap		SLBGE		PLBFL		AntHocNet	
min	max	min	max	min	max	min	max
0.0973	0.1311	0.0345	0.0402	0.0669	0.0899	0.05933	0.07106
0.1008	0.1291	0.0330	0.0395	0.0714	0.0885	0.06061	0.07389
0.1015	0.1299	0.0321	0.0385	0.0665	0.0874	0.05718	0.07095
0.1020	0.1336	0.0340	0.0413	0.0749	0.0943	0.05795	0.07114
0.0996	0.1371	0.0331	0.0398	0.0679	0.0950	0.06133	0.07451
0.1063	0.1276	0.0346	0.0383	0.0732	0.0898	0.06091	0.06976
0.1074	0.1334	0.0339	0.0387	0.0756	0.0940	0.06117	0.07144
0.1070	0.1299	0.0344	0.0400	0.0785	0.0944	0.06241	0.07420
0.1056	0.1309	0.0335	0.0403	0.0787	0.0940	0.05723	0.07030

Table 19
Medium values obtained for PLR at 20 packets/s.

PLR	AP	SLBGE	PLBFL	AntHocnet
2	0.0771	0.0565	0.0707	0.0664
3	0.0763	0.0558	0.0694	0.0649
4	0.0752	0.0553	0.0708	0.0625
5	0.0777	0.0569	0.0714	0.0658
6	0.0745	0.0562	0.0705	0.0642
7	0.0769	0.0562	0.0696	0.0643
8	0.0771	0.0559	0.0717	0.0655
9	0.0776	0.0566	0.0700	0.0665
10	0.0773	0.0559	0.0707	0.0650

Table 20
Confidence intervals for 95% of the PLR at 20 packets/s.

Ap		SLBGE		PLBFL		AntHocNet	
min	max	min	max	min	max	min	max
0.0725	0.0818	0.0531	0.0599	0.0658	0.0755	0.0626	0.0702
0.0717	0.0809	0.0520	0.0595	0.0647	0.0741	0.0615	0.0683
0.0707	0.0797	0.0511	0.0594	0.0663	0.0752	0.0589	0.0661
0.0727	0.0826	0.0533	0.0606	0.0666	0.0762	0.0616	0.0700
0.0704	0.0785	0.0531	0.0593	0.0673	0.0738	0.0605	0.0680
0.0731	0.0807	0.0536	0.0588	0.0665	0.0726	0.0613	0.0672
0.0731	0.0812	0.0526	0.0592	0.0684	0.0751	0.0619	0.0691
0.0734	0.0819	0.0533	0.0598	0.0660	0.0739	0.0623	0.0706
0.0734	**0.0811**	**0.0527**	**0.0591**	**0.0671**	**0.0744**	**0.0613**	**0.0687**

Table 21
Medium values obtained for NRO at 20 packets/s.

NRO	AP	SLBGE	PLBFL	AntHocnet
2	2.9551	2.4801	2.8445	8.7302
3	2.9575	2.4679	2.8330	8.4513
4	2.9345	2.4606	2.8421	8.6436
5	2.9767	2.4866	2.8547	8.4940
6	2.9282	2.4912	2.8558	8.1986
7	2.9704	2.4902	2.8422	8.0469
8	2.9980	2.4966	2.8986	7.9545
9	2.9951	2.5094	2.8599	7.6538
10	2.9954	2.5099	2.8835	8.3908

Table 22
Confidence intervals for 95% of the NRO at 20 packets/s.

Ap		SLBGE		PLBFL		AntHocNet	
min	max	min	max	min	max	min	max
2.8577	3.0524	2.4016	2.5586	2.7377	2.9513	8.4074	9.0529
2.8694	3.0456	2.3968	2.5390	2.7370	2.9291	8.1884	8.7141
2.8567	3.0122	2.4044	2.5169	2.7735	2.9107	8.4156	8.8717
2.8782	3.0752	2.4174	2.5557	2.7560	2.9535	8.2374	8.7506
2.8529	3.0035	2.4297	2.5527	2.7800	2.9316	8.0054	8.3918
2.8992	3.0415	2.4387	2.5418	2.7820	2.9025	7.8578	8.2360
2.9305	3.0655	2.4411	2.5522	2.8337	2.9635	7.7622	8.1467
2.9175	3.0727	2.4401	2.5786	2.7802	2.9395	7.4509	7.8567
2.9205	3.0703	2.4534	2.5664	2.8192	2.9478	8.2026	8.5790

Table 23
Medium values obtained for BLI at 20 packets/s.

BLI	AP	SLBGE	PLBFL	AntHocnet
2	0.3017	0.2590	0.3163	0.2614
3	0.3151	0.2875	0.3063	0.3045
4	0.3366	0.2897	0.3219	0.2891
5	0.2903	0.2563	0.3254	0.2917
6	0.3249	0.2598	0.3093	0.2778
7	0.3179	0.2849	0.3334	0.3049
8	0.3241	0.2748	0.3342	0.3154
9	0.3173	0.2974	0.3102	0.3039
10	0.3221	0.2852	0.3154	0.2945

Table 24
Confidence intervals for 95% of the BLI at 20 packets/s.

Ap		SLBGE		PLBFL		AntHocNet	
min	max	min	max	min	max	min	max
0.2506	0.3528	0.2092	0.3088	0.25231	0.38028	0.2091	0.3137
0.2632	0.3670	0.2464	0.3285	0.24138	0.37118	0.2506	0.3585
0.2895	0.3837	0.2248	0.3547	0.25696	0.38685	0.2288	0.3494
0.2158	0.3649	0.1845	0.3281	0.26447	0.38641	0.2251	0.3583
0.2592	0.3906	0.2021	0.3174	0.24065	0.37788	0.2160	0.3396
0.2665	0.3694	0.2501	0.3198	0.27817	0.38858	0.2588	0.3509
0.2813	0.3668	0.2294	0.3203	0.28138	0.38694	0.2673	0.3635
0.2735	0.3612	0.2496	0.3452	0.26672	0.35367	0.2585	0.3494
0.2668	0.3775	0.2357	0.3348	0.26189	0.36890	0.2438	0.3452

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