

An Application of Genetic Fuzzy Systems for Wireless Sensor Networks

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Abstract—Wireless sensor networks (WSNs) are composed of sensor nodes in order to detect and transmit features from the physical environment. Generally, the sensor nodes transmit information to a special node called sink. Some recent researches have led to the selection of routes in sensor networks with multiple sink nodes. The approach proposed by this paper presents the application of Genetic Fuzzy System (GFSs) for the selection of routes in WSNs, in order to make the communication between multiple sensor nodes and sink nodes. The results obtained through simulations demonstrated a sensor network with a longer lifetime, through the choice of the adequate sink used for sending packets through the network in order to find the best routes.

Index Terms—Fuzzy Inference System, Genetic Algorithms, Wireless Sensor Networks, Mamdani, Sink Nodes.

I. INTRODUCTION

In recent years we have witnessed a considerable increase in researches involving Wireless Sensor Networks (WSNs) due to their applicability to various areas like safety, health, agriculture, smart environments, industrial automation, among others [1],[2]. Some of the most common paradigms of communication in WSNs involve the communication of multiple sensor nodes placed in an observation area reporting information to a special node named sink (many-to-one). In [3] it is said that the use of a unique sink represents a bottleneck in a network, especially for applications in real-time and continuous data flow. In this sense, some researches have directed studies to the use of multiple sinks, in which communication addresses an alternative paradigm composed of multiple sensor nodes to multiple sinks (many-to-many). For instance, we can cite some papers that address the aspects of WSN with multi-sinks: Tradeoff Between Security and Communication Cost [4], Data Dissemination of Emergency Messages in Mobile Multi-sink Wireless Sensor Networks [5], Topology Control Algorithm Based on Bottleneck Node for Large-Scale WSNs [6], Data Caching Based Queries in Multi-sink Sensor Networks [7].

The approach used in this work focuses on the communication between the sensor nodes and the multiple sink nodes of a WSN. This scenario was chosen because of the growing popularization of applications that require networks with multiple sinks, for example, applications using multimedia

wireless sensor networks [8] applications using acting nodes [9], as well as other applications where there might be more than one sink node. Some of these applications intended to promote the selection of routes in WSN, such as: An Energy Efficient Load-Balanced Multi-Sink Routing Protocol for Wireless Sensor Networks [10], Routing in Wireless Sensor Networks Using an Ant Colony Optimization (ACO) Router Chip [11], NSN based Multi-Sink Minimum Delay Energy Efficient Routing in Wireless Sensor Networks [12].

One approach often used to deliver data to multiple sink nodes involves the technique of load balancing [13]. In this approach the data collected by the sensors are distributed throughout the network in order to use all the paths available for routing algorithm. However, the isolated use of the technique of load balancing does not guarantee the energy efficiency of the network, because the path may serve more than one sensor node and thus can have paths with different energy levels. Thus, this technique can force a particular sensor node using a route with low energy capacity.

The methodology implemented in this work for routes selection in WSN combines fuzzy inference systems (FIS) of Mamdani [14] and Genetic Algorithms (GA) [15]. We employed a FIS of Mamdani, in that we tried to model approximate reasoning [16] in order to imitate the human ability to make reasonable decisions in an environment of imprecision, uncertainties and noise. This is because FIS are potentially able to express and process qualitative information. In this paper, fuzzy inference systems of Mamdani are used to determine the most appropriate sink node through consideration of some characteristics of the sensors network, such as energy and number of hops. The production rules in an inference model have linguistic variables both in their antecedents as in their consequents. Genetic Algorithms are employed to obtain the optimal adjustment of fuzzy inference system parameters. By applying GAs, we intend to achieve both a fuzzy database and a fuzzy rules base to maximize performance of the application of Mamdani's inference system in the selection of routes in Wireless Sensor Networks. Therefore, the obtained fuzzy system should be able to help the routing algorithm to choose the best communication path between the sensor nodes and the

sink nodes so as to maximize the network lifetime. The design of a fuzzy inference system can be seen as an optimization problem in a high-dimensional search space where each point represents a specific fuzzy rule base and a fuzzy data base. The performance of the FIS forms a hypersurface in the search space. Implementing the optimal FIS corresponds to obtain the optimal location of this hypersurface. However this hypersurface is infinitely large, nondifferentiable, complex, noisy, multimodal and deceptive [17]. It is important to highlight that GAs are global optimization algorithms, based on natural selection mechanisms and genetics, which have shown themselves efficient in a wide variety of problems, in that they override many limitations found in the traditional search/optimization methods [18]. The systems achieved from the integration between the fuzzy inference models and genetic algorithms are called Genetic Fuzzy Systems (GFSs) [19].

II. RELATED WORKS

In [3] we have a wireless sensors network consisting of multiple sinks arranged in a cluster that use a database management system distributed in each sink of the network. This proposal requires two modifications in the routing protocol: the first is that the protocol should enable the creation and storage of the multiple routes during message propagation, and the second requires that the network offer QoS (Quality of Service), for the delivery of event notification messages. While the message is propagated through the network, the paths are created and stored in each clusterhead (CH).

The research in [20] proposes a scheme based on Fuzzy Logic to select a better path and increase survival time in MANETs (Mobile Ad hoc Networks). This proposal presents, as contributions, an adaptive path selection scheme and protocol independent. In addition, the correlation of the network characteristics and the safety criterion are made through the use of Fuzzy Logic, to improve the path selection in order to minimize safety limitations found in routing protocols.

In [21], the scenario is of a flat WSN that has only one sink and investigates problems of optimization of the data routing to the sink, based on metrics to choose the best path. In this proposal, a fuzzy inference system is used to select the best candidate node to send packets to the sink at any given time. One drawback to this protocol is the fact that it does not approach the use of multiple sinks, what makes it vulnerable to problems such as bottlenecks and greater energy waste of the nodes next to the sink.

Our work differs from the ones mentioned, since it was proposed to use a Genetic Fuzzy approach to enable choosing the best path for sending data. We propose an algorithm that works together with a routing protocol, in order to help the sensor node in the selection process of the best path among the various possible routes at a given time. This route selection process is made through the use of a Mamdani's fuzzy inference system responsible for classifying routes based on criteria, like energy and number of hops, with the aim of increasing the uptime of the network, since bad ways, such as longer paths, with little energy, should be avoided.

III. THE ALGORITHM PROPOSED TO ASSIST THE CHOICE OF THE BEST ROUTE IN MULTI-SINK ENVIRONMENTS

A. General Aspects

In our proposal we consider a network in which the sensor nodes are positioned so as to reach the coverage of the whole area and the multiple sinks are arranged according to the network design. It is noteworthy that the sink nodes are devices with superior characteristics to the sensor nodes, having no energy limitations.

Each sink node is responsible for receiving notification messages of events occurring anywhere on the network. For such, each sensor node must select the most appropriate sink at a given moment, taking characteristics of the network into consideration, such as energy, number of hops, collisions and delay. We must emphasize that on this paper we considered initially only two characteristics, energy and number of hops, main metrics considered in WSNs [22].

It is important to highlight that choosing a routing protocol is necessary, since our solution will work together with it. The choice of the routing protocol is made according to the needs of the network designer, being required only that the protocol be capable of providing multiple paths (multipath). To test, we used the routing protocol Directed Diffusion [23] whose operation is detailed in section 5.

B. The Solution Proposed

We present the steps of the implemented algorithm by means of Figure 1. After the positioning stage of all nodes in the network, they are started and the sinks generate a V -list containing their neighbor nodes. This list is used by the sinks to send a signalling message β^n , as illustrated in Figure 1. The signalling message sent by the sinks is propagated through the network by the neighbor sensor nodes.

At receiving a signalling message a sensor node X will check the following fields:

- *Energy*: this field is used to store the lowest energy value found on the course so far;
- *Base_station*: indicates which sink originated the signalling message;
- *Number_of_hops*: distance traveled in hops from the sink which originated the message to the current sensor node;
- *Predecessor_node*: identifies the node from which X node received the message;
- *Last_sequence*: identifies the signalling message. Every time sinks need to reconstruct the routes, a new signalling message is generated and the field *Last_sequence* will be incremented, so that the nodes may distinguish the current message from the messages sent previously.

If a given node Y receives a signalling message whose value of the field *Predecessor_node* is different from some of the neighbor nodes that it uses as the current route it will disregard this message discarding it, so as to save resources of the sensor node such as: processing, storage and energy used. Figure 2 illustrates a situation of signalling message discard in which the network interconnection has already been established at

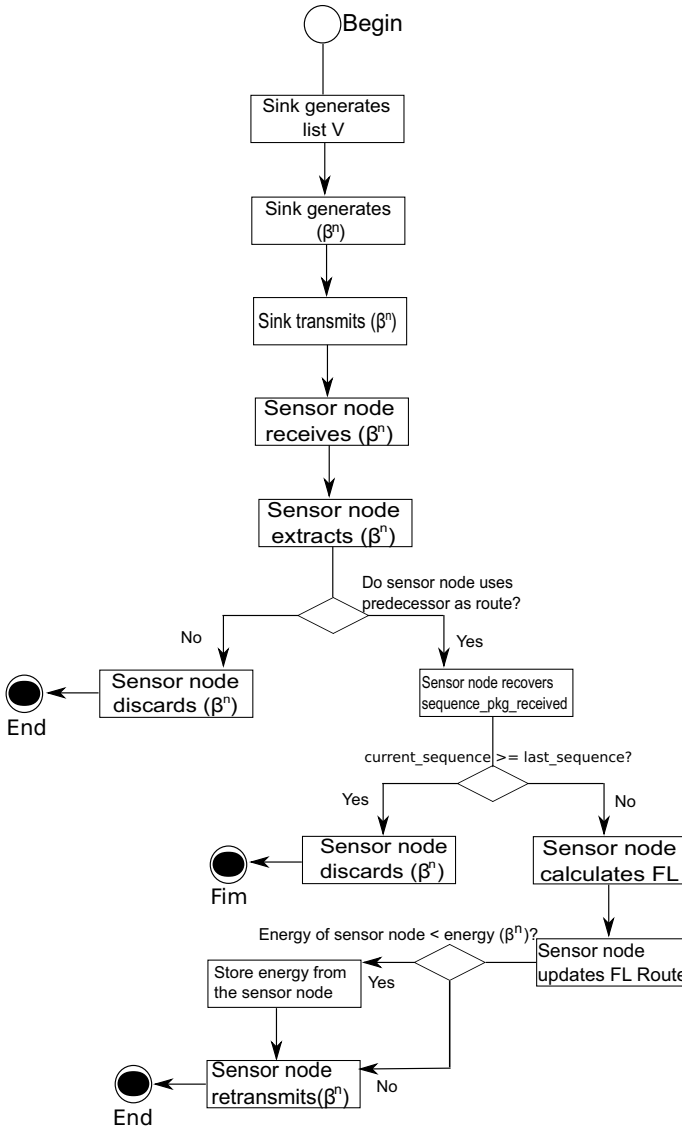


Fig. 1. Flowchart that represents the algorithm.

the boot by the routing algorithm used and the sensor nodes have multiple routes. Thus, the sensor node *Y* has two routes to reach the sink node established through the nodes *X*, *id* = 1 and *W*, *id* = 2. When the signalling message β^n is transmitted by the sink node, the neighbor nodes propagate the message through the network. Thus, when node *Z* receives the message β^n , it passes it on to all neighbor nodes it can reach, including sensor nodes that are not part of its route, as it is the case of node *Y*, when receiving the message β^n from node *Z* will discard it immediately.

In order to avoid old messages from remaining traveling through the network, some routines are established according to algorithm presented in Figure 1. A given node *X* at receiving a signalling message checks the field *Last_Sequence* to verify whether it refers to a new signalling message, or if it is only the propagation of a message received previously. The next step is to calculate the fuzzy level (FL) associated with each

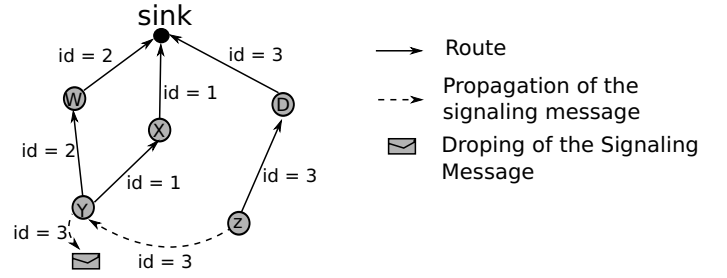


Fig. 2. Dropping of the signalling message.

route. This parameter allows the node to select the best route at a given moment, according to the last signalling message received. For each route that a node may use, there is an FL associated with it. Routes with higher FL value are regarded as preferential. The FL value is obtained through Mamdani's fuzzy inference model, whose entries correspond to the values of energy and number of hops. Finally, node *X* tests if its energy is lower than the energy contained in the received message, if so, it updates the field energy signalling message with the value of its remaining power, if not, it goes to the next step and relays the message over the network.

In our work, we consider that each sink node will send signalling messages β^n periodically to the network, in order to update the FL of each route set up by the routing algorithm. Thus, there will be a better use of the energy of the sensor nodes, in that the routes are chosen at each transmitted signalling message. We call α window the period in which signalling messages are transmitted. The value attributed to α cannot be very small so that the network is overcharged with the constant transmission of signalling messages nor can it be a value large enough to affect the choice of routes. Details related to the α value determination will be submitted in section 7.

IV. GENETIC FUZZY SYSTEM

A. Fuzzy Inference Systems

Fuzzy Inference Systems are able to handle very complex processes, based on imprecise, uncertain and qualitative information. Fuzzy Inference Systems are very suitable for modelling complex systems where it is very complicated to describe the system mathematically. Generally, the fuzzy inference systems are based on linguistic rules of type "if ... then" in which the fuzzy set theory [24] and the Fuzzy Logic [25], [26] provide the mathematical basis.

In general, fuzzy inference systems operate based on three steps: Fuzzification, inference procedures, and defuzzification. In fuzzy inference systems, generally, non fuzzy (quantitative, accurate, crisp) inputs are taken into consideration, derived from observation or measurement, which is the case of most practical applications. Fuzzification is a mapping of the domain of the entrance variable to the fuzzy domain, representing the attribution of linguistic values defined by membership

functions to the input variables of the Fuzzy Inference System. The fuzzy inference procedure is responsible for evaluating the primary terms (linguistic labels) of the input variables applying the production rules so as to obtain the value of the fuzzy output from the inference system. Once the fuzzy output set has been obtained at the step of defuzzification an interpretation of that information is made. This step is necessary because in practical applications, quantitative outputs are generally required. Defuzzification is typically used to assign a numeric value to the output fuzzy set.

B. Genetic Algorithms

Genetic Algorithms are search and/or optimization algorithms based on the mechanisms of genetics and natural selection. Their operation follows biologic inspiration, which presupposes that in a given population individuals with “good” characteristics are more likely to survive and to beget even stronger individuals (fit), while the less fit individuals tend to disappear during the evolutionary process. When using GAs, each individual of the population, called chromosome, represents a potential solution to the problem to be solved. Each piece of the chromosome is called the gene. GAs emphasize combination of the most promising candidates for the solution of the problem. This combination of the fittest individuals is obtained through the application genetic operators that manipulate the genetic composition of chromosomes in order to explore and to exploit the search space so as to find better solutions to the problem. The genetic operators mentioned are computational approximations of phenomena seen in nature, such as genetic mutation and sexual reproduction.

Though apparently simple, in part due to their bioinspired foundation, GAs are able to solve complex problems in very elegant way. Moreover, they are not affected by suppositions about differentiability or continuity of the objective function of the problem, in that GAs do not use information from derivatives in the evolutionary process, nor do they need information about the individuals’ neighborhood. This implies that GAs can be very appropriate to deal with problems with non-differential and non-continuous functions. In addition, GAs differ themselves from randomic search and/or optimization techniques, since they apply the fitness index, which is important information relevant to the search space obtained by the use of the evaluation function.

C. Genetic Fuzzy System Implementation Aspects

The implemented fuzzy inference system has two input linguistic variables, Energy and number of hops, and a output linguistic variable, the Fuzzy Level (FL). The syntax of the rules of the fuzzy system is represented by the following linguistic conditional declarations:

- Rule 1: If (Energy is A_1) and (Number of hops is B_1), Then (FL is C_1) or
- ...
- Rule n_r : If (Energy is A_p) and (Number of hops is B_q), Then (FL is C_r)

where: n_r is the number of rules; A_j , B_k , C_l are the primary terms (linguistic values) associated with the linguistic variables, Energy, number of hops and FL, respectively; p , q and r correspond to the number of primary terms of the linguistic variables Energy, Number of hops and FL, respectively.

Thus, we have a Mamdani’s fuzzy system, consisting of N_r disjunctive inference rules. The rules are inferred in a parallel way, without considering the order in which they are implemented. The inference of each rule consists of the evaluation of the antecedent, followed by the application of the implication operator to determine the consequent fuzzy set. The defuzzification procedure obtains the FL’s numeric value. The implication operator used was Mamdani’s minimal operator; the aggregation of the consequents was performed by the maximum operator and the defuzzification method employed was the area center method (or centroid method) [27], [28].

The approach adopted in this paper proposes the use of GAs to determine the number of primary terms for the linguistic variables, the adjustment of the membership functions associated with each primary term, and the set of linguistic rules of Mamdani’s fuzzy system, simultaneously.

The first aspect to be considered in the use of GAs for the solution of a problem is the chromosomal representation of the problem, so that the GAs can solve it appropriately [17]. In this study the chromosomes have information related to the number of primary terms and the membership functions of the input and output linguistic variables, as well as information on the rules bases of the fuzzy inference system.

The chromosome structure to store the parameters of the fuzzy inference system was divided into three parts. The first part codifies the amount of primary terms of the linguistic variables. This part of the chromosome has 9 bits, where each set of 3 bits represents the number of primary terms of a linguistic variable. The second part stores information of the fuzzy rules base. According to experience of authors in relation to the behavior of WSNs, the top number of primary terms of each linguistic variable was defined as being equal to 5, and the amount of rules is then set by a multiplication between the numbers of primary terms of the input linguistic variables (Energy and Number of hops). Thus, the maximum number of rules in the system is equals to 25. Therefore, the second part is represented by 75 bits, and each set of 3 bits represents the primary term associated with a rule of the inference system. The third part codifies the parameters of the membership functions of each linguistic variable of the system. As membership functions have continuous parameters that require a great precision, the representation of the chromosome by real numbers was adopted [29], instead of binary representation [30] used in the two first parts. The membership functions used for the linguistic variables are triangular (Figure 3).

However, instead of the chromosomes storing the values a_i , m_i and b_i for each membership function, they store the adjustment coefficients (parameters) δ_i and η_i . Each membership function i can be assembled from the following equations [31]:

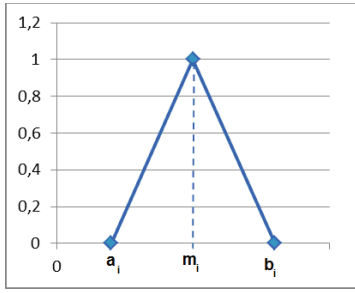


Fig. 3. Triangular membership function.

- $a_i = (a_i + \delta_i) - \eta_i$;
- $m_i = (m_i + \delta_i)$;
- $b_i = (b_i + \delta_i) + \eta_i$.

The coefficient δ_i is responsible for moving the membership function to the right or to the left, while the coefficient η_i can expand or shrink the support of the membership function [28] in relation to its universe of discourse. As each linguistic variable has 5 primary terms at most, and each membership function associated with a primary term is represented by the two parameters δ_i and η_i , 10 genes, at most, are necessary to represent the membership functions of a linguistic variable of the applied fuzzy inference system. Therefore, the third part of the chromosome has size 30. As each chromosome stores the information about the parameters of the inference fuzzy system (fuzzy database and fuzzy rule base), we have one chromosome of 114 ($9 + 75 + 30$) genes. The GA implemented has adopted a population of 80 individuals (chromosomes).

After the chromosome representation definition, the GA design focuses on the specification of an evaluation function. Since the goal of the fuzzy system is to help the routing algorithm choose the best way to communicate between the sensor nodes and the sink nodes, this work employed the time it takes for the first sensor node of the network to die as evaluation function. Therefore, this is a maximization problem whose objective is to tune the Mamdani's fuzzy inference system that selects the best routes to maximize the lifetime of the network.

After the attribution of the fitness index by the evaluation function, the selection process chooses a subset of individuals of the current population to compose an intermediate population in order to apply the genetic operators. The selection method adopted in this work was the tournament method. It is worth mentioning that the size of the adopted tournament was set equal to 2. In combination with the selection module an elitist strategy was used with the maintenance of the best individual from one generation to the other.

To evolve the population go through an evolution one should apply the genetic operators (crossover and mutation). Crossover is the process for sharing information through of the exchange of portions (genes) of the parent chromosomes. The crossover operator has always been considered as the primary search operator in GAs because it exploits the available information from chromosomes about the search space. As

this operator combines the features of parent chromosomes to form offsprings, it is highly probable that good chromosomes may generate better ones. Therefore the crossover can be considered one of the main components for improving the behavior of the GA [32]. In this study, we used discrete crossover [33]. The mutation genetic operator [34] is necessary to introduce and maintain genetic diversity of the population through randomic changes of genes within the chromosomes, what provides a means for incorporation of new genetic characteristics within the population. Therefore, mutation ensures the possibility of reaching any point of the search space, besides to avoid to get trapped in local minima. However, mutation is applied less frequently than crossover in order to preserve the exploration-exploitation-relationship [35].

Several criteria may be applied to finalize the execution of a GA. In this work the maximum limit of generations fixed in 100 interactions was adopted as stopping criterion.

As a result of the GAs operation in the adjustments of fuzzy systems, Figures 4 and 5 show the membership functions associated with the linguistic variable energy and number of hops.

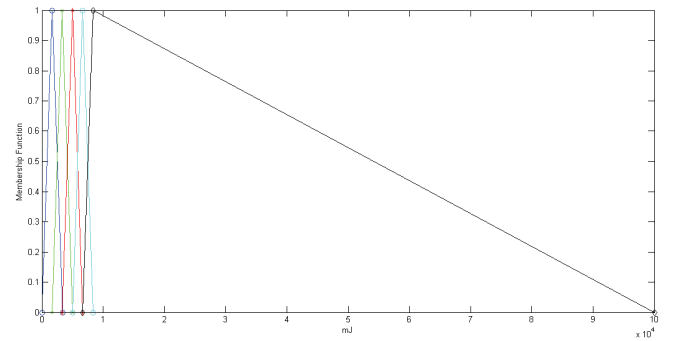


Fig. 4. Membership function of the energy variable.

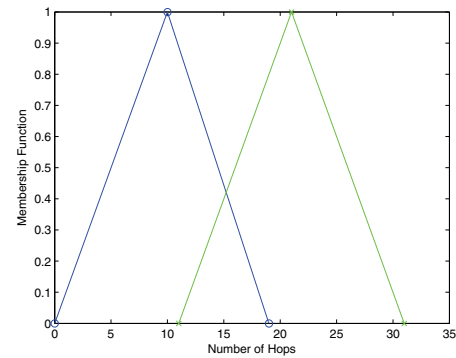


Fig. 5. Membership function of the number of the hops variable.

V. SIMULATION

This section presents comments about the simulations carried out to validate the routes selection algorithm using the implemented Genetic Fuzzy System.

A. Simulator

In our experiments, we use the Sinalgo simulator [36]. Sinalgo is a framework implemented in Java language, for testing and validating the networks algorithms. Contrary to other tools such as the *Network Simulator 2* [37], which allows the simulation of networks in several layers of the protocol stack, our approach focuses the use of Sinalgo to verificate the efficiency of the algorithms to selection of routes.

B. Network Characteristics

The main characteristics of the network are:

- 1) Topology: the simulated network is steady and includes only two types of nodes: sink nodes and sensor nodes. The sensor nodes have similar characteristics, featuring a flat network, where each node of the network has a single identifier and steady radio range.
- 2) Scenarios used: in our simulations we used four scenarios with similar environment. All scenarios are usually composed of 100 sensor nodes distributed uniformly throughout the network and for the scenarios that use multiple sinks we used 4 sink nodes located at the end of the network initially, with a range area of 700 m x 700 m. We configured a sensor node located in the center of the network to transmit packets continuously at a ratio of one packet per second in the four scenarios.

Next we describe the simulated scenarios:

- Scenario 1: in this scenario we used the Directed Diffusion routing protocol in its traditional form, without the use of fuzzy inference systems and without multiple sinks.
- Scenario 2: we used the Directed Diffusion routing protocol with multiple sinks and applied the load balancing among the existing multiple paths. It is important to emphasize that we did not use Fuzzy Inference Systems.
- Scenario 3: the application through Mamdani's fuzzy inference system influences the routes formation through the Directed Diffusion protocol, in order to choose the best route to one of the sinks. Nevertheless, the design of the fuzzy inference system is made in an empiric way, in which the adjustments of the fuzzy database and the fuzzy rule base are made manually, based on tests with various different configurations.
- Scenario 4: just as in scenario 3, the application through Mamdani's fuzzy inference system influences the formation of routes through the Directed Diffusion protocol, in order to choose the best route to one of the sinks. However, in this scenario, the parameters of the fuzzy inference system are not adjusted empirically anymore, but by using Genetic Algorithms, characterizing the approach as fuzzy-genetic.

C. The Routing Algorithm

For the communication of the nodes with the sinks, we used the Direct Diffusion routing protocol, which is designed for wireless sensor networks, where the network designer

is responsible for defining the type of event that should be observed by the sensor nodes and the area of interest.

VI. RESULTS AND DISCUSSIONS

The results of the proposed approach application are presented based on three metrics. The metrics are:

- First node death time: it expresses the death time of the first node in the network. Here, we intend to analyze how long sensor nodes remain living;
- Network death time: it records how long the network remains alive, that is, how long the network will be able to keep the necessary communications active.
- Sink nodes number: in this metric, we evaluate how the amount of sink nodes influences our work;

Although our solution is aimed at environments with multiple sinks, we firstly analyzed the network behavior through simulations in the same scenarios described in section V using only one sink node, as illustrated by the figures 6 and 7. We conducted these experiments with the purpose of verifying the feasibility and efficiency of the proposed solution, since an environment with a single sink did not receive satisfactory results, possibly the realization of these simulations environments with multiple sinks would be unsatisfactorily similar.

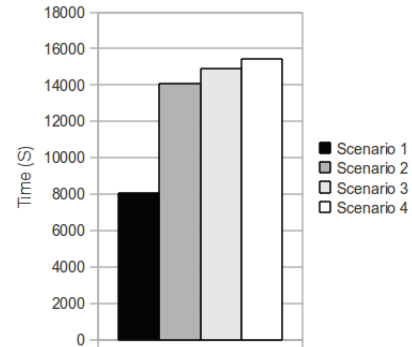


Fig. 6. Death time of the first node of the network.

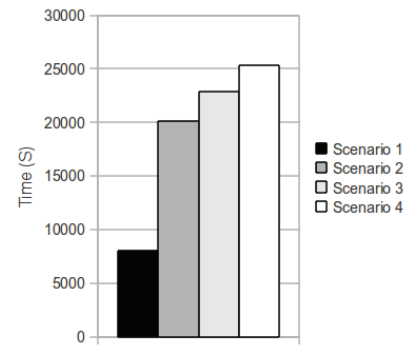


Fig. 7. Death Time the Network.

We also evaluated the behavior of the sensors in a WSN with multiple sink nodes for each scenario according to the three metrics addressed. For the first metric, first node death time

in the network, we can see from Figure 8 that in scenario 1, where we used the Directed Diffusion protocol in its traditional form, without the use of fuzzy inference systems and without multiple sinks. The results showed weakness in the lifetime of the network, where a sensor node participates actively in a route in use. In scenario 2, without using Fuzzy Inference Systems, with multiple sinks and the usage of load balancing. We obtained an improvement of approximately 11% compared to scenario 1. In scenario 3 we have a solution that uses fuzzy inference systems adjusted empirically, associated with the use of multiple sinks. In this scenario, the gain compared with scenario 1 is approximately 234%. Finally, in scenario 4 we have the representation of the proposed solution that uses a genetic fuzzy system and multiple sinks in which the gain when compared with scenario 1, approaches 373%. This gain was due to the use of multiple sinks, increasing the number of routes each node can use for the transmission of data over the network and the use of the genetic fuzzy system which makes the node avoid the bad routes (low energy, long distances).

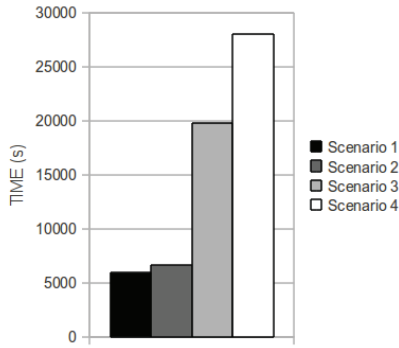


Fig. 8. Death time of the first node of the network.

We represented in Figure 9 the network death time, time when the network communication is discontinued due to the death of some sensor nodes that compose the routes of the sender. In the column representing scenario 1 (without fuzzy inference system and without multiple sinks), we have that the network death time corresponds to the network's first node death time because this network does not have multiple routes and multiple sinks. In scenario 2, due to load balancing across multiple paths to network remains active around 104% more than scenario 1. In scenario 3, the network remains active for a long period of time. Approximately 478% higher than the scenario 1, this gain was achieved by using multiple routes, associated with the use of empirical fuzzy inference in the best routes selection process at a certain moment. The great difficulty encountered in this simulation scenario was due to the empirical adjustment of the inference system that consumed much time, in that they were carried out based on trial and errors. Still, it was not possible to firmly tell whether the chosen parameters of fuzzy inference system were the best. We obtained in scenario 4, an uptime of the network higher than all simulated scenarios; about 541% higher than scenario 1, this gain was promoted through the use of genetic fuzzy

system and multiple sinks.

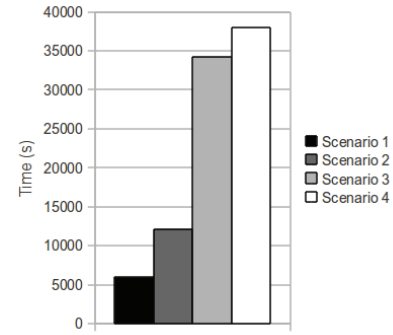


Fig. 9. Death Time the Network.

VII. α WINDOW

As mentioned previously, in our algorithm, we consider that each sink node waits for an α time window to send signalling messages so that the sensor nodes update their fuzzy levels.

We conducted simulations with different α values and we evaluated the performance based on the network's first node death time (Figure 10). We could realize that the values close to the desired are between 800 and 900 seconds.

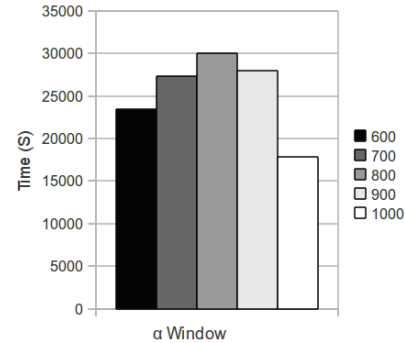


Fig. 10. Window α .

VIII. CONCLUSIONS

This paper proposes a fuzzy genetic system-based algorithm for the selection of routes in WSN with multiple sinks. Fuzzy inference systems of Mamdani are used to determine the most appropriate sink node through consideration of some characteristics of the sensors network, such as energy and number of hops. However, the optimal design of a Mamdani's fuzzy inference system is a complicated task due to some characteristics of the search space. Generally, this search space is characterized as infinitely large, nondifferentiable, complex, noisy, multimodal and deceptive. These characteristics induce the authors to apply Genetic Algorithms on tuning of Mamdani's fuzzy inference system. The main objective of the algorithm is to extend the network's lifetime which can be achieved by making the nodes avoid bad routes during the sending of packets through the network. For such, we applied

fuzzy inference systems in order to build a knowledge base which makes the process of finding the best routes possible.

Results obtained through simulations, demonstrated that our approach is feasible increasing the network's lifetime satisfactorily. In future works we intend to analyze the behavior of algorithms in more complex scenarios, as well as select new linguistic variables for the fuzzy inference.

When you opt for a fuzzy inference system to determine the selection of routes in a wireless sensor network with multiple sink nodes, you have an action/control strategy that can be monitored and interpreted, even from the linguistic viewpoint. Another advantage found in using fuzzy inference systems during the development of this work refers to the inclusion of the authors' experience in the definition of some parameters of the implemented fuzzy system. That experience could be used directly to aid the construction of the rules base and the initial definition of the primary terms (fuzzy sets) of the linguistic variables.

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