A Fuzzy Inference System for Increasing of Survivability and Efficiency in Wireless Sensor Networks

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***Abstract*—The nodes of a Wireless Sensors Network (WSNs) are composed of small devices capable of sensing and transmitting data related to some phenomenon in the environment. These devices, named sensor nodes, have severe constraints, such as lower processing and storage capacity, and, mainly, they have severe constraints related to battery energy. Therefore, the developing of strategies to reduce the power consumption is one of the main challenges in WSNs, and thereby helping to increase the survivability and efficiency of these networks. This paper proposes a new approach to help multi-path routing protocols to choose the best route based on Fuzzy Inference Systems and ant colony Optimization (ACO). The Fuzzy System is used to estimate the degree of the route quality, based on the number of hops and the lowest energy level among the nodes that form the route. The Ant Colony Optimization (ACO) algorithm is used to adjust the rule base of the fuzzy system in order to improve the classification strategy of the route, and hence increasing the energy efficiency and the survivability of the network. The simulations showed that the proposal is effective from the point of view of the energy, the number of received messages, and the cost of received messages when compared against other approaches.**

***Keywords-WSN*; *Energy*; *Routing*; *Fuzzy Inference Systems*; *Ant Colony Optimization*; *Sink Nodes*.**

I. Introduction

Wireless sensor networks (WSNs) consist of a large number of sensor nodes distributed over a geographic area. Each node belonging to the network has the property to sense and transmit events, such as: luminosity, humidity, atmospheric pressure, pollution levels, temperature, among other. It is import to stress that each node has one or more sensors, processing capacity, storing and communication.

The WSN has motivated the interest of the research community because of its applicability in many areas, for instance, household applications [1], medical [2], military, environmental, farming [3] and vehicular environments. The WSNs differ from the traditional networks in many aspects, such as: the WSN are composed of a large number of sensor nodes; sensor nodes have a limited power supply, lower processing capacity and memory. In addition, some WSN applications require self-organization, in which the nodes must adjust themselves in an autonomous way, responding to structural changes, due to failure in some equipment, battery depletion, or by an external user request.

According to Araujo et al. [4], the main goal of a WSN is to collect data from the environment and transmit this data to a special node, called sink-node. In addition, the WSNs must provide some interface to permit the extraction of this information by external entities (i.e., users, or others information systems). Because of the sensor nodes limited power supply, the energy consumption is a relevant factor at all the stages of the life cycle in WSN applications [5].

Communication in WSNs consumes more energy than processing and sensing performed by the network nodes. An important challenge in WSN field is the energy consumption reduction, since in most cases these nodes are deployed in a harsh environment, making hard the battery replacement. The importance of energy consumption in WSNs is also depicted by Pinz et al. [6]. The authors have showed that transmission is the main cause of energy consumption.

This feature requires the implementation of routing policies that enable the sensor nodes to communicate efficiently and effectively with minimum power consumption. For this reason, the routing protocols must work with information based on the quality of routes, related to relevant network metrics, such as the energy level of the network sensor nodes.

Thus, the routing protocols for WSNs must have self-configuration properties, enabling to find out which is the best way to transfer information, considering the guaranteed delivery and energy level among the nodes of the network. If a sensor node will fail due to lack of energy, routes must be

 ISBN: 978-1-61208-245-5

recalculated, so that the information collected can reach the destination node. The communication between the sensor nodes must optimize the energy consumption in order to increase the lifetime of the network.

This work proposes a Fuzzy Inference System [7], [8] to help the Directed Diffusion routing protocol [9] to choose a route for the communication between any nodes in the network. The Directed Diffusion was chosen because of its wide acceptance in current works and the multi-path properties. The proposed fuzzy system uses as input to the inference process, the number of hops and the lowest energy level among the nodes that comprise the route. From the quantitative values of the inputs, the system estimates a quantitative value associated with the quality of each route, in order to assist the routing protocol in the selection of several feasible routes. Therefore, based on the quality of the route, the routing protocol should define which route to be used for sending the data collected with the aim of increasing the network lifetime.

The design of a fuzzy inference system can be seen as a search/optimization problem in a search space of high dimensionality (multidimensional). Each point of the search space represents a particular fuzzy knowledge base (fuzzy database + fuzzy production rules base). Therefore, finding the best design of a fuzzy inference system means to obtain an optimal point on the search space. However, this search space is characterized as infinitely large, non-differentiable, complex, noise, multimodal and deceptive [10]. Thus, obtaining a fuzzy inference system optimized for a particular application can be a very complex task. In the proposed approach, the adjustment of the Fuzzy Inference System for classification of routes is performed automatically by the Ant Colony Optimization (ACO) algorithm [11]. ACO is a computational model for optimization inspired by the foraging behavior of real ants [12]. Specifically, ACO algorithms are based on the ability of real ants for finding the shortest path from their nest to the food source by exploiting pheromone information. Pheromone is a chemical substance layed by real ants while walking. Paths that have higher concentrations of pheromone have more chances to be followed by the other ants. Therefore, the pheromone plays an important role by biasing the decision mechanism of the real ants. By following a specific path, the ants lay its own pheromone in order to reinforce the pheromone concentration. Based on trail-laying and trail-following mechanism, the real ants can find the shortest path connecting the nest and the food source.

The main benefits of the proposed approach are:

- Application of fuzzy inference systems for inferring the quality degree of routes. Therefore, the process for calculating the quality degree of each route can be accompanied and tracked from the linguistic viewpoint. Additionally, fuzzy inference systems are able to express and manipulate qualitative information, which can help the domain experts in understainding the results produced;
- As sensor nodes have limited resources, the sink nodes are responsible for calculating the quality degree of each route. This means that the fuzzy inference system is executed inside the sink nodes instead of inside sensor nodes. The sink nodes are not strongly limited as the sensor nodes;
- Application of an ant colony optimization algorithm for adjusting the rule base of the fuzzy inference system. The ACO algorithm implemented is the Ant System [13]. As a heuristic algorithm, ant colony optimization does not require special properties of the search space such as convexity, smoothness, existence of derivatives. Additionally, ACO algorithm is a population-based technique and includes stochastic components to update the solutions which results in lower chances of the optimization process to get trapped in local minima. It is noteworthy that the rule base stores the strategy of action/control implemented on the fuzzy system. Therefore, an optimal adjustment of the rule base must result in an efficient strategy for dealing with the limited resources in a WSN;
- Besides the use of pheromone information by artificial ants, a heuristic function is used for enhancing the process of constructing solutions to the problem. Although ACO algorithms are able for solving problems without using a heuristic function [14], the incorporation of a heuristic information normally results in better solutions [15]. The use of a heuristic function requires specialized information related to the problem being solved. For this purpose, the experience of the expertise in WSNs is used as heuristic information for guiding the construction of solutions by artificial ants;
- In order to represent realistically the behavior of a Wireless Sensor Network, an energy dissipation (consumption) model is applied in the proposed approach. Most of the works in WSNs are focused on the routing protocols itself, without taking into account the energy consumption that happens in the sensor nodes [16]. The sensor nodes are highly dependent on the limited battery source for its communication (data collection and transmission) and computation operations [17]. Since energy is drawn for both operations, it is important to consider the rate at which the energy is consumed for both operations. As the energy consumption in transmission is greater than the consumption in computation operations, the majority of the works only handles the consumption of energy during the communication. Therefore a energy consumption is included for avoiding misleading calculation to the overall energy consumption of the WSN.

The article is organized as follows: Section 2 presents a description of the problem to be solved. Section 3 describes the proposed approach. The evaluation of results is discussed in Section 4, followed by conclusions in Section 5.

II. Routing in Wireless Sensor Networks

A. Routing Protocol

The Directed Diffusion [9] routing protocol was used for the communication between the sensor nodes and the sink nodes, which is designed for Wireless Sensor Networks where the network designer is responsible for defining the type of event that must be observed by sensors and monitored area [5], [18], [19], [20].

Directed Diffusion protocol has its operation based on the following elements: named data, interest, gradient, and reinforcement. Data are named by using a pair (attribute, value) and represent an event detected by the sensor nodes. The interest is the phenomenon that represents the search attributed to the network. The gradient is the pointer that represents the reverse path addressed to the sink node. The task to be sensed is diffused by the sensors network through a interest message sent by the sink node through periodic broadcasts. The interest messages can be originated by one or more sink nodes, according to the network design. Because of this feature, interest messages, when disseminated by the network, create gradients, which are states stored by the sensor nodes that have received interest messages, identifying the nodes that sent interest. Thus, the gradients define the nodes that should receive data related to the disclosed interests. Finally, there is the reinforcement, where the sink node receives messages from events occurring at a low rate of transmission through various available paths, and then it chooses one of these paths and reinforces the transmission rate for the event to be informed through this path at a higher transmission rate. The sink performs reinforcement by resending the original interest to the selected path, forcing the data source node (node that detected the event) to increase its transmission rate of data collected through this path.

Figure 1 illustrates some aspects of Directed Diffusion. The propagation of interest is shown in Figure 1 (a), at this initial moment, the sink node broadcasts over the network a interest message containing the named data (attribute, value) from which it wants to receive information. The interest message is periodically updated by simply changing the time stamp of interest. This is necessary because the sensor network is not reliable in transmitting packets.

After broadcasting the interest message, sensor nodes in the network associate gradients to each interest message received, creating routes between the sink and the data source node, as shown in 1 (b). Through the use of interests and gradients, several paths are established between the sink node and source node, but only one of these paths is selected by the reinforcement mechanism, as illustrated in Figure 1 (c).

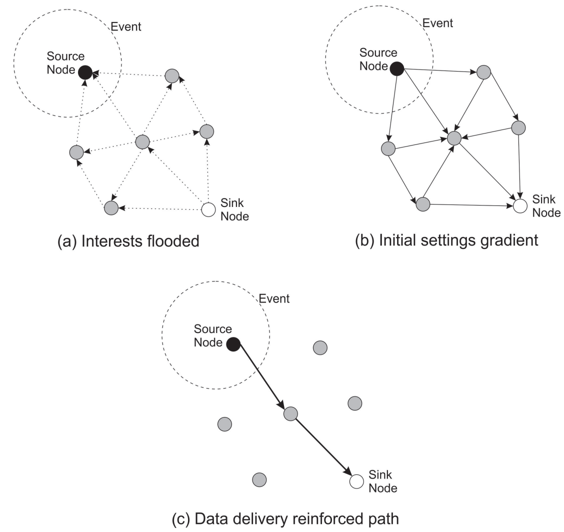

Figure 1. Directed Diffusion

The Directed Diffusion protocol meets dynamic networks by a trading scheme with the spread of interest and reinforcements paths, allowing the network to converge before any topological change. Moreover, the Directed Diffusion uses delay as a metric for route choosing, which usually is the better choice.

A disadvantage of this approach is the high cost of communication for route repair when failures occur due to the need of periodically broadcast in network in order to reinforce others routes.

B. Related Works

A proposal for optimization of energy consumption is treated in Chan et al. [21]. The idea of this proposal is to put some sensor nodes in sleep mode (off) to conserve energy while maintaining connectivity between the nodes that comprise the network. This strategy has the benefit of energy savings due to switching execution between sensor nodes.

Shah and Rabaey [22] describe the protocol EAR (Energy Aware Routing). The basic operation is the occasional use of a set of paths chosen by a probability function (which is dependent on the power consumption of each path). This prevents that the best route has its energy exhausted. Therefore, the network lifetime is increased. It is assumed that each node has an address and information about your location. This proposal has advantages due to which route selection is performed by probability function allowing the selected route is not used until the death of the nodes that make up said route.

A fuzzy expert system for clustering of sensor nodes [23] is presented with the target of conserving energy. Three linguistic variables are employed in the design of fuzzy expert system, including the selection probability, the

 ISBN: 978-1-61208-245-5

distance from the base station, and the sum of the distances between the selected node and the other nodes with lower energy than the average energy.

Most of the energy consumed in WSNs is the transmission of data to the sink node. Singh et al. [24] propose mobile sink to minimize power consumption. The movement of the sink is determined by the mechanism based on fuzzy logic. The authors state that the base station can only move in a predefined circular path in accordance with input variables, such as the node residual energy, and distance to the base station. The simulation results are compared with the methods that have a stationary base station.

A hybrid approach involving a Mamdani fuzzy system optimized with Genetic Algorithms is presented in [25]. The hybrid intelligent system is employed to assist the routing protocol Directed Diffusion [9]. The sensor nodes have a fuzzy inference system implemented, which is tuned by a Genetic Algorithms, resulting in a fuzzy-genetic system [26]. The fuzzy system set is used to estimate the quality of each route associated with the sensor node. The results show that the use of genetic fuzzy system in conjunction with the protocol Directed Diffusion increases the lifetime of the network protocol when compared to Directed Diffusion without the use of fuzzy systems. However, the proposed approach does not consider a dissipation energy models in the sensor nodes, i.e, the approach does not account consumption (dissipation) of energy during the calculation of the degree of quality of the route through fuzzy inference system (fuzzification, inference procedure and defuzzification). The adoption of a dissipation energy model would make the processing more realistic, since the fuzzy system is implemented in sensor nodes, reducing the level of battery power consumption.

III. PROPOSED APPROACH

A. Fuzzy Inference System

Fuzzy inference systems are capable of dealing with highly complex processes, which are represented by qualitative information. Normally, fuzzy inference systems are based on linguistic rules of the type “if condition then action”, in which the fuzzy set theory [27] and fuzzy logic [28] provide the necessary mathematical basis to deal with qualitative information and with the linguistic rules.

A fuzzy inference system, generally, is composed by four components (Figure 2):

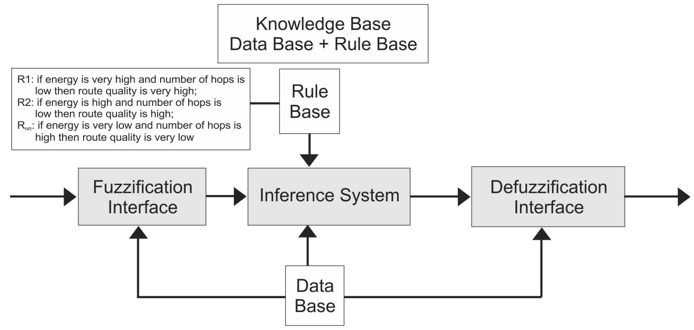

Figure 2. Fuzzy Inference System

- Fuzzification Interface: responsible for mapping the quantitative input variable to the fuzzy domain, representing the assignment of linguistic values (primary terms), defined by membership functions, to the input variables;
- Knowledge Base: is formed by two components, the Data Base and the Rule Base. The data base contains the primary terms for each variable considered in the linguistic rules and the membership functions associated to each primary terms. The rule base is comprised of linguistic rules that determine the policies of control-action strategy and decision-making. The rule base realizes the mapping from the input domain to the output domain, and this way, plays an important role to generate the results produced by the fuzzy inference system;
- Inference System: responsible for evaluating the primary terms of the input variables, by applying linguistic production rules contained in rule base, in order to obtain the fuzzy output value of the inference system. Therefore, the fuzzy output value is function of the rule base specified;
- Defuzzification Interface: responsible to assign a numerical value to the output fuzzy value. Thus, defuzzification can be considered a kind of synthesis of the final fuzzy output set by means of a numerical value.

B. Ant Colony Optimization

Ant Colony Optimization (ACO) algorithms constitute a relevant subset of ant algorithms. ACO is composed of algorithms for optimization/search problems and is inspired on observations of how some ant species forage for food. Therefore the ACO meta-heuristic concerns about developing algorithmic models of the foraging behavior of real ants. Besides of the complex behavior for foraging, other collective behaviors of real ants that have been proposed and applied include the division of labour, cemetery organization, brood care and construction of nests.

The emergence of shortest path selection in foraging behavior is explained by the differential path length effect and autocatalysis (positive feedback, reinforcement learning through pheromone deposit) [11], [15].

The ACO algorithm involves two basic procedures:

- Procedure for building a solution, in which Na (number of ants) ants build in parallel way Na solutions to the problem.
- Procedure for updating the pheromone concentration. The built solutions by the ants are evaluated through

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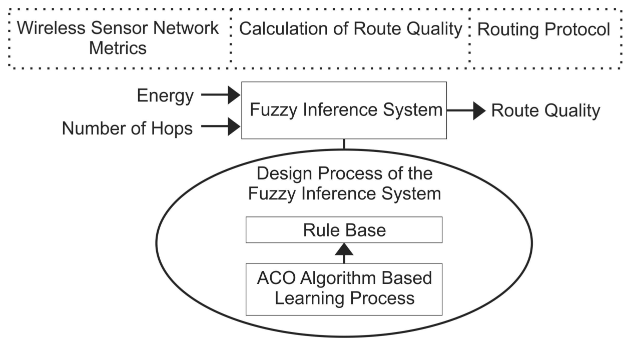

Figure 3. Design Process of the Fuzzy Inference System

an evaluation function in order to measure the quality of the solutions produced. The update of the pheromone concentration is based on the evaluation function, this way, better solutions result in more pheromone deposited in its parts.

C. ACO Algorithm for Adjusting the Rule Base of the Fuzzy Inference System

In our approach, an Ant Colony Optimization algorithm has been used for adjusting in an optimal way the rule base of the fuzzy inference system. This way, the tour of an artificial ant is regarded as a combination of primary terms to the output linguistic variable (route quality) from every rule of the rule base. Therefore, for each rule, N_{pt} linguistic values are available to be selected, where N_{pt} is the number of primary terms for the output linguistic variable. During its tour, the ant has to choose one primary term for each rule from a total of N_{pt} options. This way, the complete specification of the rule base of the whole fuzzy inference system is given by the tour of an ant. Suppose that N_r is the number of linguistic rules present on the rule base, there are $N_{pt}^{N_r}$ combinations associated to the output linguistic variable. As the rule base relates the mapping of input values to the output value, an optimal adjustment of the rule base enhances the results produced by the fuzzy inference system. For our purpose, the result produced by the fuzzy inference system is the quality degree of the routes (route quality). As better the result produced by the fuzzy system, higher is the lifetime of the WSN. Our target is to find the best combination that maximizes the performance of the fuzzy inference system to classify the routes at the WSN. Therefore, after the training phase (learning process) via ACO algorithm, the fuzzy inference system is optimally adjusted and is ready to be incorporated in a sink node of a real Wireless Sensor Networks for classifying the routes associated to itself (Figure 3). The route quality is used by the routing protocol for selecting a specified path to send a message.

The fuzzy inference system proposed has two input variables: the lower energy level associated to some sensor node of a determined route and the number of hops necessary for sending the message to the sink node. The definition of the partition fuzzy for each input variable has been made in advance, based on the knowledge of the expertise. 5 primary terms were defined for the variable related to the lower energy level, and 3 primary terms were defined for the variable associated to the number of hops. This way, the rule base contains 15 rules. The output variable which determines the quality degree of the route has 5 primary terms. Therefore, for each rule, 5 options are available for the linguistic value. The artificial ants have to find an optimal setting for the linguistic rules from a total of 5^{15} (30517578125) combinations.

Besides of using artificial pheromone to help the choice of a specified path by the ants, the Ant System algorithm incorporates a heuristic function. The inclusion of an heuristic information normally results in better solutions but requires specialized information related to the problem being solved. The problem of designing the heuristic information is solved by using the expertise knowledge. Therefore, the accumulated experience of the expertises is used for helping the decision-making process by the ants.

The main aspects involved with the optimization of the fuzzy rule base are:

- Initialization of the parameters: at this step, the parameters of the ACO algorithm are initialized. The number of ants, the evaporation rate, the parameters that control the relative importance of pheromone information versus heuristic information.
- Initial placement of the ants: all the ants are placed on the start node which can resemble the nest.
- Selection of the primary term for each rule: the ants execute a probabilistic decision-making concerning what node should be visited. The decision-making process is based on the pheromone information and heuristic function. The primary term represented through the selected node by the ant is inserted in the linguistic value of the associated rule. This way, the selection of the primary term represents the process of building a solution which is equivalent to determine the primary term for each rule.
- Evaluation of the built solutions (produced tours): after the ants finish the solution construction process, it is necessary to measure the obtained solutions. The evaluation of the produced solutions is used for determining the quality of the solutions with respect to the problem being optimized. This way, it is possible to indicate what ant adjusted better the rule base. For evaluating the solution produced by a specific ant, the rule base obtained is inserted in the fuzzy inference system and a simulation of the WSN is realized. The lifetime of the WSN is used as the value for measuring the quality of the fuzzy inference system because this value represents the energy level of the sensor nodes. Therefore, as

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higher the lifetime of the WSN, better is the rule base obtained.

- Updating of the pheromone concentration: in the last stage, the ants deposit their own pheromone. The pheromone deposited is proportional to the lifetime of WSN. Therefore, the highest value of pheromone deposited is obtained by the fuzzy inference system that classified better the routes and this way extends the lifetime of the WSN.

IV. Results and Discussions

In order to verify the applicability of the proposed approach, the Sinalgo simulator [29] has been used. Sinalgo is a framework developed in Java that allows the simulation of wireless network, abstracting the lowest layers of the protocol stack. The proposed solution is compared to the Directed Diffusion routing protocol (DD) and the Directed Diffusion routing protocol with a fuzzy inference system (DDF) incorporated, but designed in a manual way. The simulator scenario was designed to allow a didactic comprehension of the proposed algorithm, with a topology containing 10 X 10 sensor nodes. The initial energy stored at the battery was considered equal to 1,0 Joule. The simulations took into account the energy consumption model proposed in [30] and used in [17]. It is noteworthy that the fuzzy inference procedures for obtaining the route quality are realized at sink nodes, therefore the cost of the energy consumption associated to fuzzy operations (fuzzification, inference and defuzzification) is not considered because the sink nodes are not limited for energy. However, the cost for receiving, processing and sending messages is taken into account at all sensor nodes.

We choose the following four metrics in order to evaluate the proposed approach (DD-ACO-Fuzzy), against the Directed Diffusion (DD) and Directed Diffusion with fuzzy system manually adjusted: number of received messages, residual power, number of received messages versus time simulation, and the cost of incoming messages. The number of received messages corresponds to the amount of incoming messages versus the time simulation measured on rounds (time scale of the simulator). The residual power measures the amount of remaining power in the sensor node after sending messages to the sink node. The number of received messages versus the time simulation corresponds to the amount of messages that the sink node received during the network simulation. The cost of incoming messages is the ratio between the consumed power and the amount of received messages into the sink node. The network lifetime is the elapsed time between the start of the simulation till the moment that the sink node is unable to receive messagens collected and sent by the network.

Figure 4 shows that using the proposed approach in this work, the number of received messages into the sink node versus the time is greater than in the DD and DDF

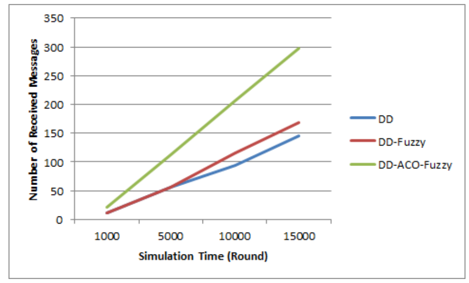

Figure 4. Number of received messages into the sink node versus the time

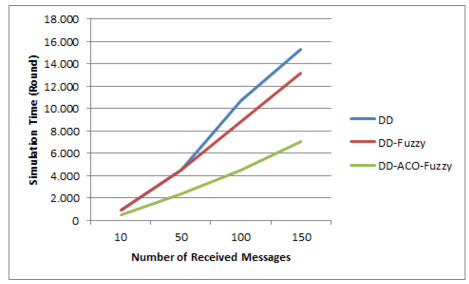

Figure 5. Simulation time necessary for a specified number of received messages

approaches. This way, the proposed approach is able to increase the number of messages for the same simulation time. This means that a highest number of messages is capable of be transmitted, which maximizes the benefits of the limited resources of the sensor nodes. The Figure 5 complements the Figure 4 by showing the necessary time for the other approaches be able to receive the same number of messages received by the DD-ACO-Fuzzy. The proposed approach reaches a higher amount of delivered messages to the sink node during the simulation and requires a lowest quantity of time for receiving a specified number of messages. The difference was about 8,000 rounds.

The remainder amount of power in the sensor nodes after the receiving of messages into the sink node is greater with the DD-ACO-Fuzzy approach, as showed in the Figure 6. This is reached because the proposed approach guarantees a higher delivery rate by selecting smartly the route with the lower number of hops and the greater residual power of the sensor nodes along the route. Therefore, the routing protocol uses an information, the route quality, which is inferred from the number of hops and the residual power of the sensor nodes. The route quality is adjusted whenever the network conditions (metrics) are modified. This adjustment increases the reliability of the route quality because it takes into account instantaneously any modifications in energy level of the sensor nodes, for instance.

The Figure 7 shows that the cost of incoming messages, using the DD-ACO-Fuzzy approach, is decreased of approximately 60% if compared against the Directed Diffuzion and Directed Diffusion Fuzzy approaches. Therefore, a lowest

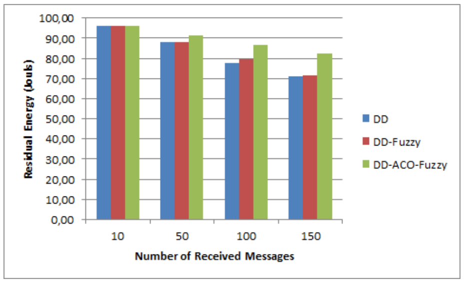

Figure 6. Residual power (energy) in the sensor nodes for a specific number of received messages

Figure 7. The cost of incoming messages

cost for the message communication is realized by using the proposed approach. This implies that a highest level of energy will be available which results in a highest life time for the wireless sensor network.

V. Conclusion and Future Work

This work proposes a Fuzzy Inference System to help the Directed Diffusion routing protocol to choose a route for the communication between any nodes in the network. The proposed fuzzy system estimates a quantitative value associated with the quality of each route, in order to assist the routing protocol in the selection of several feasible routes. Therefore, based on the quality of the route, the routing protocol should define which route to be used for sending the data collected with the aim of optimizing the network lifetime, the number of received messages, the necessary time to send a specified number of messages and the cost of received messages. As a hard task, the adjustment of the Fuzzy Inference System for classification of routes is performed automatically by the Ant Colony Optimization (ACO) algorithm. The ACO algorithm is used for adjusting the rule base of the fuzzy inference system. The rule base stores the strategy of action/control implemented on the fuzzy system, and therefore, an optimal adjustment of the rule base must result in an efficient strategy for dealing with the limited resources in a WSN.

The results showed that the Directed Diffuzion with Fuzzy approach using the ACO algorithm, for all metrics, is more efficient than the others, showing positive results with relation to the amount of received messages, residual power, number of received messages verus time simulation and the cost of incoming messages. Therefore the inclusion of a fuzzy inference system is capable of improving the use of limited computational resources associated to a wireless sensor netowrk. Although the use of a fuzzy inference system adjusted by trail and error approach (DD-Fuzzy) makes a better use of informations to classify the routes, this kind of adjustment is not so powerful as the automatic adjustment by ACO. The ACO algorithm is able to explore the search space and identify good regions to be exploited, in order to optimize the benefits of using a fuzzy inference system for helping a routing protocol. As future works, the authors are applying ACO algorithms for a simultaneous adjustment on fuzzy data base and fuzzy rule base.

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 ISBN: 978-1-61208-245-5