Connectivity Control in WSN Based on Fuzzy Logic Control

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***Abstract*—The connectivity of a wireless sensor network (WSN), specified as the percentage of nodes that are able to reach the base station (BS) that relays nodes data to other networks, has to be kept as high as possible, without either increasing significantly the energy consumption or worsening the WSN overall performance. Modelling accurately a WSN and designing a control system for accomplishing the desired network connectivity is an effortful task. In this paper, an approach based on fuzzy logic control is proposed, as it provides a better trade-off between accuracy, effort and time. The control system running in each node will manage both the communication range to guarantee a minimum number of neighbors called *node degree*, and the *node degree* itself, depending on the node's battery level at each moment. The fuzzy controller running in a node will monitor the own node's parameters, without flooding WSN with monitoring messages.**

I. Introduction

One of the target when designing, deploying and exploiting a Wireless Sensor Network (WSN) is to maximize the number of nodes that are able to transmit or receive data to or from the base station (BS) in such a network, considering the BS as an element in the network acting as a gateway between the WSN and any other data networks. Unfortunately, the number of connected nodes in a WSN (nodes that are able to send or receive data to or from the BS) would decrease over time as nodes relaying messages crash or fail due to hardware failures, battery discharge, software bugs and so forth.

There are several approaches and strategies that will minimize such risks and will improve the WSN connectivity. Most of them are high resource consuming as nodes are checking their availability of reaching a BS from time to time. The network is flooded with control messages that impact negatively on the performance and the energy efficiency of all the nodes in the path. There are others, like the one presented in the following sections, that provide a better trade-off between the network connectivity and the resource consumption. The strategy in this paper aims at keeping constant the node degree (ND) of a node, its number of neighbors. The node degree depends on the WSN deployment (regular, random, etc.), the area to be covered and the number of nodes. So, the desired node degree will be calculated for the specific WSN to be deployed and that value will become the target of the self-adaptive system. Intuitively, if a node has a higher degree (indicates more neighbors), it is more likely that there are at least one path for it to transmit data to the destination. If all nodes are randomly and uniformly deployed, the probabilistic approach to analyze the relation between the node degree and the network connectivity is fully described in [1].

The self-adaptive system presented in this paper aims to control the communication range of each node to manage its degree, in order to recover the link when its neighbors fail. Whenever a node's neighbor fails, the communication range of that node is increased to replace the failing neighbor. Therefore the node's energy consumption is likely to increase. If the desired node degree, whose value is estimated before the nodes deployment as mentioned above, is kept constant all the time, the battery might become exhausted too short. Thus, the desired node degree has to be adjusted in run time taking into account the battery level and the desired lifetime of autonomous nodes. Note that directly changing communication range usually is not feasible, instead the transmission power is the parameter can be controlled in real sensor nodes. In this paper, we employed the transmission power model in the literature [2], in which the transmission power is linear function of square of the communication range.

The basic idea of the control system is that if the node degree is higher than the expected node degree, then the communication range has to be decreased; if the node degree is lower than the expected node degree, then the communication range has to be increased. The desired node degree will depend on the energy of the node. How fast and how long the communication range changes, is decided by the controller, e.g. fuzzy logic based controller.

II. Control System Design and Evaluation

A. Control System Design

The control of the node degree increases the robustness of the network (or reliability) and also the network connection probability [1], [3], [4]. This parameter could be controlled by varying the transmission power or communication range of the node. The relation between those variables has been characterized by a probability density functions, they have nonlinear dynamic relation and is highly topology depending [1], [5].

An alternative to face this issue is to design a control system based on single feedback loops for self-adaptation of communication range against dynamic changes in the links with the neighboring nodes. A basic feedback control loop should contain a function of decision-making (FDM) which provides a variation factor of the communication range (Δcr) as output and the node degree error (e_{ND}) as input (i.e. the difference between the desired value ND_R and the real one ND). Figure 1 describes a graphical representation of the relationship between the node degree and the variation on its communication range. The communication range of node N_1 at consecutive sample instants is represented by the dashed circles and the node degree are the number of links (solid line) with its neighboring nodes. The disk model is widely adopted to simplify the radio model, although the communication range is more likely to be irregular [6], omnidirectional [7], or asymmetric [8] in reality. However, the disk model does not directly have negative impact

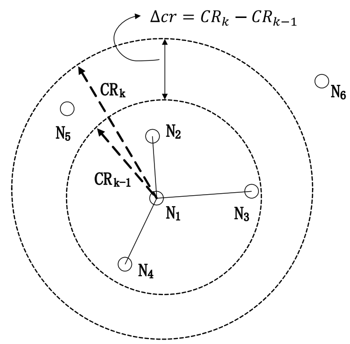


Figure 1. The relation between variation of the communication range and the node degree.

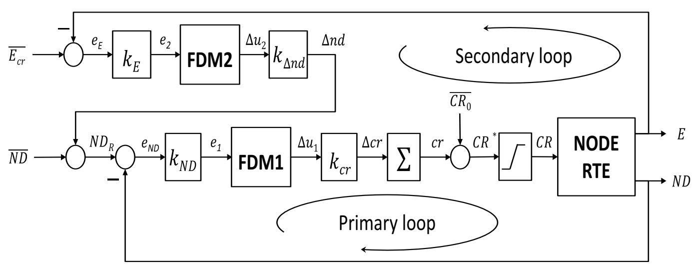


Figure 2. Reconfiguration loops for a self-adaptive communication range.

on our controller design, because the controller inputs that needed to measure are node degree and energy, rather than communication range.

Additionally, another single feedback loop can be added to perform the task of modifying the desired value for the node degree according to the battery level (E). The aim of this action is to reduce the device power consumption when the battery is under a certain energy critical level ($\overline{E_{cr}}$). A reduction of the node degree means to reduce the device communication range by reducing the signal transmission power. Hence, this represents a reduction of the energy consumption and an increment in the battery lifetime. The controller (FDM hereinafter) of this loop receives the difference between a battery critical level ($\overline{E_{cr}}$) value and the actual battery level (E) as input.

Figure 2 illustrates both reconfiguration closed loops with two FDM strategies, a "primary" loop for the calculation of Δcr (**FDM1**) and another or "secondary" loop to determine the desired or reference value of the node degree (**FDM2**).

Within the **primary reconfiguration loop**, the communication range can be updated at certain time instant k as follow:

$$e_{ND}(k) = ND_R(k) - ND(k) \tag{1}$$

$$e_1(k) = k_{ND} e_{ND}(k), \quad \Delta cr(k) = k_{cr} \Delta u_1(k) \tag{2}$$

$$\Delta u_1(k) = f_{DM1}\big(e_1(k)\big) \tag{3}$$

$$\begin{aligned} CR^*(k) &= cr(k) + \overline{CR_0} \\ cr(k) &= cr(k-1) + \Delta cr(k) \end{aligned} \tag{4}$$

$$CR(k) = \begin{cases} CR_{min}, & CR^*(k) < CR_{min} \\ CR^*(k), & CR_{min} \leq CR^*(k) \leq CR_{min} \\ CR_{max}, & CR^*(k) > CR_{min} \end{cases} \tag{5}$$

At the above equations, $\overline{CR_0}$ is the initial value of the communication range and f_{DM1} represents the **FDM1** function. The function input e_1 is the normalized node degree error and the output Δu_1 is the normalized communication range variation factor. Also, the value of CR is saturated between its minimum value CR_{min} and maximum value CR_{max}. k_{ND} and k_{cr} are normalization or scale factors for the input and the output respectively. Both factors can be calculated as:

$$k_{ND} = 1/\overline{ND}, \quad k_{cr} = \overline{\Delta cr} \tag{6}$$

where $\overline{ND}$ represents the nominal or desired value of the node degree when the battery has a critical energy level ($\overline{E_{cr}}$). Factor $\overline{\Delta cr}$ is the communication range variation rate.

The **secondary loop** tunes the desired value for the node degree according to the battery level and can be formalized as follow:

$$e_E(k) = \overline{E_{cr}} - E(k) \tag{7}$$

$$e_2(k) = k_E e_E(k), \quad \Delta nd(k) = k_{\Delta nd} \Delta u_2(k) \tag{8}$$

$$\Delta u_2(k) = f_{DM2}\big(e_2(k)\big) \tag{9}$$

$$ND_R(k) = \overline{ND} + \Delta nd(k) \tag{10}$$

where e_E is the difference between the battery critical level and the actual level and Δnd is the node degree variation factor. Besides, f_{DM2} represents the **FDM2** function where its input e_2 is the normalized or scaled value of e_E and output Δu_2 is the scaled node degree variation factor. k_E and $k_{\Delta nd}$ are scale factors for the input and the output respectively. Both factors can be calculated as:

$$k_E = 1/\overline{E_{cr}}, \quad k_{\Delta nd} = \overline{\Delta nd} \tag{11}$$

where $\overline{\Delta nd}$ is the node degree variation rate.

In general terms, both loops can be seen as a function which receives the actual values of ND and E as inputs, returning a new value of CR as output and requiring a set of parameters $\overline{\mathbf{P}}$:

$$\begin{aligned} CR(k) &= g\big(ND(k), E(k), \overline{\mathbf{P}}\big) \\ \overline{\mathbf{P}} &= \Big[\overline{CR_0}, \overline{ND}, \overline{E_{cr}}, \overline{\Delta cr}, \overline{\Delta nd}, \\ & \qquad CR_{min}, CR_{max}\Big] \end{aligned} \tag{12}$$

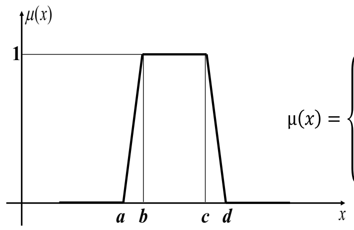
where the complete parameters list is: initial value of the communication range ($\overline{CR_0}$); desired value of the node degree when the battery has a critical energy level ($\overline{ND}$); critical energy level ($\overline{E_{cr}}$); communication range variation rate ($\overline{\Delta cr}$); node degree variation rate ($\overline{\Delta nd}$); minimum and maximum value of the communication range (CR_{min} and CR_{max}).

B. Decision-Making based on Fuzzy Logic

The relation between the input (e) and the output (Δu) for both decision making functions (f_{DM1} and f_{DM2}) can be as simple as:

$$\Delta u = \begin{cases} -1, & e < 0 \\ 0, & e = 0 \\ 1, & e > 0 \end{cases} \tag{13}$$

However, in order to handle with uncertainty in certain points of the input variable space, we can divide it into regions with fuzzy boundaries between them and therefore use Fuzzy Logic as



$$\mu(x) = \begin{cases} 0, & x \le a;\ x \ge b \\ \dfrac{x-a}{b-a}, & a \le x \le b \\ 1, & b \le x \le c \\ \dfrac{d-x}{d-c}, & c \le x \le d \end{cases}$$

Figure 3. Trapezoidal-shape distribution function and probability density function.

mathematical tool for decision making [9], [10]. In the specific case of the proposed control system, and according to the classification for fuzzy linguistic controller (FLC) proposed by Wang et al. [11], in the primary loop the fuzzy algorithm will be used for feedback error/output control (Type 2 FLC) and in the secondary loop for input selection task (Type 1 FLC).

As equation (13) suggests, the input space can be partitioned in three regions or fuzzy sets (FS): negative values (NV), zero values (ZV) and positive values (PV). The degree or probability of membership of a value of e at certain instant k to any partition can be calculated with a probability distribution. Some of the candidate distributions very well known in the literature related to decision-making based on fuzzy logic (FL-DM) are the Gaussian distribution, triangular-shape distribution, a trapezoidal-shape distribution or the generalized bell distribution [12].

Due to its simplicity for implementation and its low computational load of mathematical operations, the trapezoidal-shape probability distribution is a good candidate to define the input regions. Figure 3 describes the probability density function and its graphic representation of the trapezoidal-shape distribution.

Employing this function we can define a distribution or membership function (MF) for each partition. The boundaries of each fuzzy partition and the parameters of its probability density function is defined in Table I.

Fuzzy set	MF	a	b	c	d	Boundaries
NV	$\mu_{NV}(e)$	-4	-2	-0.5	-0.25	$e < -0.25$
ZV	$\mu_{ZV}(e)$	-0.5	-0.25	0.25	0.5	$-0.25 \le e \le 0.25$
PV	$\mu_{PV}(e)$	0.25	0.5	2	4	$e > 0.25$

Table I. PARAMETERS FOR EACH MEMBERSHIP FUNCTION

Moreover, the output variable Δu can be treated in a linguistic way by assigning labels to the possible values that Δu can achieve. The output space can be defined as: function f_{NC} for negative change (NC), f_{ZC} for none or zero change (ZC) and f_{PC} for positive change (PC). According to this, equation (13) can be transformed as:

$$\Delta u = \begin{cases} f_{NC} = -1, & e \in NV \\ f_{ZC} = 0, & e \in ZV \\ f_{PC} = 1, & e \in PV \end{cases} \tag{14}$$

FL-DM function defined above has been designed and evaluated in the Matlab Fuzzy Logic Toolbox. The FL-DM function is a Sugeno type Fuzzy Inference System (FIS) of one input and one output and three rules. The algebraic product has been selected as AND logic connective for the rules precedent calculation and for rule implication and the function output value is calculated as a weighted average of all rules.

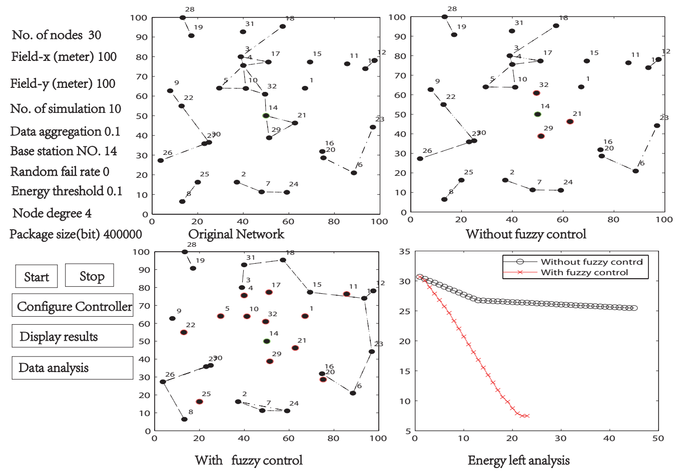


Figure 4. Matlab-based simulation tool

C. Control System Simulation and Evaluation

1) Matlab-based Simulation Environment: In order to evaluate the control system, a Matlab-based simulation tool has been implemented (see Figure 4) to facilitate the design and validation without considering the underlying WSN protocols. Our simulation tool is able to configure the control system parameters and the network parameters such as the number of the nodes to be deployed in the network, the size of the area where sensor nodes will be deployed, etc. It also visualizes the simulation process and analyzes the results once the simulations are finished.

In order to evaluate the performance of the control system, the simulation-based experimental platform were set up and configured as follows: (1) 32 sensor nodes randomly are deployed in a $100 \times 100 m^2$ area. The Base Station (BS) is always located at the centre of the deployment area. (2) Each sensor node was randomly assigned an initial communication range with values within configurable boundaries, e.g. [10,30]. (3) The node's battery is fully charged at the beginning of each simulation. (4) The deployed nodes start transmitting packages to the BS if there is a routing path available. If there are more than one paths to the BS, then the node chooses the shortest path. (5) The sensor stops sending package when it runs out of battery. (6) The whole simulation is terminated when there is no packages received at the BS side.

With the aim of comparing the network performance, the simulation tool simulates two times on the same network topology, with the same configuration parameters: the first time without control algorithm and the second time with the control algorithms on each node, e.g. control loops based on Fuzzy Logic. The sub-figures at top-left, top-right and bottom-left in Figure 4 show respectively the original deployment of the nodes, the links and status of the nodes once the simulation has ended when no control has been carried out and when the control algorithm has been running. In those three sub-figures, the x and y axis indicate the width and the length of the field. The energy consumption due to the processing of the control algorithm has been considered negligible. The energy analysis sub-figure at bottom right in Figure 4 illustrates the remaining energy of all nodes at each round.

2) Results Evaluation: In order to measure the network performance, the total number of packages received at BS (P_{BS})

Controller Parameters	Communication Range	P_{BS_NC}	P_{BS_WC}	Improvement
$\overline{ND} = 4$, $k_{\Delta nd} = 3$, $k_{cr} = 2$	R = [10,30],R_{BS} = 25	189.8	411.9	+117.02%
	R = [15,35],R_{BS} = 30	356.2	454.8	+27.68%
	R = [20,40],R_{BS} = 35	538	576.8	+7.17%
$\overline{ND} = 4$, $k_{\Delta nd} = 2$, $k_{cr} = 1$	R = [10,30],R_{BS} = 25	224.6	479.2	+113.36%
	R = [15,35],R_{BS} = 30	442.1	537.8	+21.65%
	R = [20,40],R_{BS} = 35	537.5	601.3	+11.87%
$\overline{ND} = 3$, $k_{\Delta nd} = 2$, $k_{cr} = 1$	R = [10,30],R_{BS} = 25	224.9	384.7	+71.05%
	R = [15,35],R_{BS} = 30	388.9	496.1	+27.56%
	R = [20,40],R_{BS} = 35	519.1	504.7	-2.77%

Table II. COMPARISON OF RECEIVED PACKETS AT BS (AVERAGE OF 10 NETWORKS RANDOMLY DEPLOYED)

during the whole simulation has been measured. For each set of the configuration parameters, 10 different network topologies have been simulated. The nodes for each network are randomly deployed and the simulation has been executed two times: with and without the fuzzy control-based algorithm. The results are shown in Table II where the first column is the controller parameters. The second column contains the communication range interval for each node and the communication range for the BS. The third and forth columns are the average value of P_{BS} obtained from the 10 networks deployed with the same set of parameters. The last column is the improvement percentage between the performance of the network with the control algorithm (P_{BS_WC}) and without it (P_{BS_NC}). It is calculated as: $100\% \times (P_{BS\_WC} - P_{BS\_NC})/P_{BS\_NC}$.

After an analysis of the results in the table, the following observations can be made: (1) in general, more packages were received at BS when the fuzzy control algorithm was applied; (2) the number of packages a BS receives increases directly proportional with the node degree; (3) in general the self-adaptive communication range based on fuzzy control loops improves the connectivity of the network; and (4) as shown in the first sub-row of each row, both the radius of regular nodes and BS are smallest, which would lead to worse connections at initial node deployment, but the improvement is much higher. It implies that the network shows better adaptive performance when network is not well connected at the beginning.

III. CONCLUSION

The introduction of control loops based on fuzzy logic enables each node to adjust automatically the communication range according to a desired node degree and residual energy. After comparing the performance of the network with and without the control system, in general, the number of the packages received at BS has been increased. It indicates that the network connectivity has been improved and therefore the network is more resilient to the nodes failure. However, several questions are still open. E.g., what is the energy performance of the network? In order to have an optimal balance between the performance of the network connectivity and the energy consumption, what are the optimal values of the controller parameters? How to tune the control system for different network topologies? How to adjust the desired node degree for each node independently according to its location in the network? When there is an interaction between neighbours nodes, does the control system introduces oscillations in the communication range and the connection links between nodes? If it is the case, how to avoid or reduce this oscillation? Once the control system described in this paper has been deployed in a real system, how does it impact, among others, on the memory footprint, the processor performance and the energy consumption?

All of these questions and others will be answered in future works. As a next step, an optimization strategy, based on the proposal of Haber et al. [13], will be developed for an appropriate adjustment at design time of the control system parameters. In addition, the control system will be implemented in physical devices and its performance at run time will be explored in depth.

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