Intelligent Fault Management System for Wireless Sensor Networks with Reduction of Power Consumption

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***Abstract*—In Wireless Sensor Networks (WSN), when a hardware error is not identified and promptly corrected, all monitoring of a sensor network is compromised. This work presents a new approach to centralized fault management system for 6LoWPAN WSN. The system is based on two fault detection levels. A first level is performed locally, by all sensors within the network, using statistical methods. The second level is performed by the base station, through an ensemble of Multilayer Perceptron type Artificial Neural Networks (ANN) classifiers. One of them is continuously trained with streaming data, while the other one is used to take actual decisions about fault detection. The inputs of these ANN are outputs from a Kalman Filter and from an accelerometer. Experimental results indicate that this approach is capable of reducing message traffic and power consumption within a WSN, keeping the detection accuracy rate higher than 97%.**

I. Introduction

With the development of embedded systems with low power consumption, miniaturization of electronic devices, development of protocols and communication infrastructure, Wireless Sensor Networks (WSN) have become increasingly present in our lives. It is common to find remote networked systems used for health care monitoring [1], prevention and mitigation of natural disasters [2], biodiversity management and conservation [3], smart cities [4] and smart building [5], in addition to industrial monitoring [6] and military [7]. Because WSN are often used in harsh environments, being exposed to chemical and biological agents, and working with limited energy resources, they are subject to hardware failure [8]. Therefore, if a single hardware failure happens, the whole network can be affected [9].

Fault management plays a fundamental role in the design of WSN. However, developing an efficient fault management system to WSN faces many obstacles. This is due to unpredictable behaviour of such networks, and to particular features of the applications in which they are employed [10]. For example, a WSN designed to monitor an underground system has distinct characteristics from an ocean detection system. Substantial differences between these two networks start from the environment in which each one is inserted (underground or underwater environment).

The main role of a fault management system is to provide a set of functions that allows for the network to detect, to isolate and to correct abnormal behaviour [10]. Although many fault management models in WSN present good results, as detection, diagnosis and failure recovery [11], [12], [13], [14], [15], not many studies use centralized approaches, which can reduce the exchange of messages within the network. Distributed approaches are generally seen as superior than centralized models [16]. This is because in a distributed model, the base station does not need to get all existing messages, so the power consumption within the network tends to be lower [17]. On the other hand, the complexity involved in developing a distributed system is increased. Through the use of statistical and computational intelligence techniques, the centralized management proposed in this paper aims to provide a system which includes the main features of each one of these approaches, without compromising power consumption in the network.

The contribution of this work to the state of the art is to show that we can combine the simplicity of building a centralized fault management system with reduction of the power consumption, which is normally provided by distributed fault management systems. Therefore, the proposed system maintains high accuracy in fault detection and still presents low power consumption.

This paper is organized as follows. Related reports dealing with fault management systems are discussed in Section II. Then, Section III presents the proposed fault management system and Section IV describes the experiments undertaken. Simulation results are reported in Section V, and we conclude the paper with final discussions in Section VI.

II. Related Work

Fault detection in WSN can be divided into two different approaches, centralized and distributed. In a centralized fault detection system, a base station or controller is responsible

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for monitoring the messages exchanged within the network, periodically analysing and identifying possible defective sensors. In this approach, message traffic between devices in the network tend to be high. In addition to the regular communication between nodes, the base station needs to obtain information about the functioning of each node in the network. In a distributed fault detection model, some decision-making levels are assigned to local nodes and, when a hardware failure is detected, the base station must be informed.

A centralized approach is used by [18] where the node manager can check each node by analysing the messages exchanged and the network map. Another centralized approach is found in [19] which developed a lightweight sensor network management system whose aims have a reduced impact on memory and network traffic. This system was build with two main services: a query system that cares about the network health and performance and a logging system to record and retrieve system-generated events. An approach that employed a statistical algorithm called Statistics Sliding Windows to diagnose faults and subsequently to generate a regression model that predicts potential hardware errors can be found in [20]. Statistical techniques were also used in [21]. At that work, Principal Component Analysis (PCA), in conjunction with First-Order Perturbation (FOP), were employed to detect failures and to reduce the number of messages within the network. With the use of PCA, it is possible to restrict the amount of data required for fault detection. Other centralized fault management systems are found elsewhere [22], [11], [23]. All these models showed low false positive rates, provided by the use of Fuzzy Logic.

Distributed fault detection models are found in three different approaches: node self detection, neighbour coordinator and clustering. Node self-detection occurs when a fault is detected by the faulted sensor node itself. An algorithm to detect flaws in WSN, called Node Self Detection by History Data and Neighbours (NDHN), is a good example of that approach [24]. Data collected by the sensor are compared with neighbouring historical data, to make a judgement about the possible state (normal or faulty). In neighbour coordinator approach, nodes communicate with neighbour nodes to identify faulty nodes. Using simulation, some reports showed that faulty sensor detection accuracy can be over 97% [25], [26]. In the clustering approach, the network is divided into regions that are controlled by cluster heads. These special nodes identify defective sensors by sending short messages to other nodes in the same region. If a failure is detected, a broadcast message is sent to each cluster head [27], [28], [29]. The distributed clustering approach also can be found in [30] where the authors propose a mechanism to identify a gateway failure and recover sensors that were part of this failed cluster. The system presented by [31] has centralized and distributed characteristics, introducing the concept of external managers and agent nodes. The external manager receives the data from the chosen agent nodes and analyses this collected data trying to find any failed sensors. So the work presented in [31] can be seen as a hybrid fault management architecture.

Accelerometer measurements are used to catch information about errors in many different areas. A sensor fault self-diagnosis is presented by [32], where physical malfunctions caused by impacts or incorrect orientation are detected using accelerometer measurements. [33] uses accelerometers and a set of others sensors to detect and isolate sensors that are defective in order to improve intelligent vehicle navigation. The work of Huang and Su [33] shows that accelerometer can be used to detect faults in helicopter transmissions. In this case the accelerometer measures the vibration of the transmission. When these vibration assume an abnormal behaviour, failures caused by gear tooth error can be detected. Marcal and others [34] detect faults in the operation of rotating machines based on a change of system vibration standard. Other applications of fault detection using accelerometer are found in [35], [36], [37], [38], [39].

III. Fault Management System

The fault management system proposed in this work implements a centralized fault detection model. To reduce the number of messages exchanged within the network, each sensor node has a primary role in the fault detection process. We propose an intelligent fault management system that is split into two levels. The first level of detection, called fault self-detection, is performed by each sensor node. Here, an approach similar to the one proposed by [20] is used, but with a slightly different application. Data is measured and stored in a buffer, containing thirty historical measurements taken by the node itself. From this set of stored data, a Normal distribution model is generated. Each new data acquisition is compared with the standard deviation of the Normal model. If this new measure is located more than two standard deviations apart, it is sent for analysis at the base station, as can be seen in Fig. 1. In order to prevent that the entire series of data is in a constant failure region, a random time interval is used to send a sample for analysis to the base station from time to time.

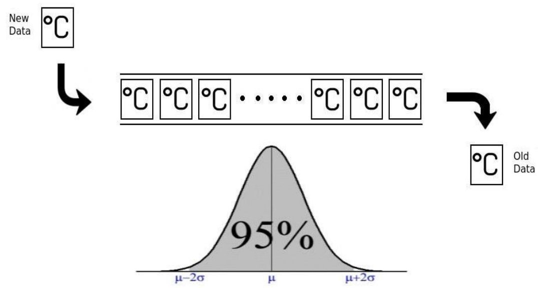

Fig. 1. Statistical fault detection scheme (first level).

On the second level, held at the base station, two ANN are employed as an ensemble. The first ANN, here called off-line classifier, is trained with historical data and, after this, it is used to decide on the proper functioning of the system. The decision making process will be described next. The second ANN, called on-line classifier, remains in training, using current data acquisition streaming. At defined time intervals, the state of the WSN is evaluated, and occasionally on-line and off-line classifiers can switch functions, with former on-line one stopping being trained, going to decision making, and former off-line network starting being trained with on-line data. A switching between these networks occurs when more than 10% of the nodes in the network are faulty, or when more than 90% of the analysed measures are classified as Normal. This switching between networks is responsible for minimizing the quality degradation of the fault pattern recognition process in the long term. Due to the dynamic characteristics of WSN, we must ensure that normal fluctuations in the measured variable will not be treated as a hardware failure.

Both ANN employed in the ensemble have two inputs and only one output. The first input is the absolute difference between the measured temperature and the temperature value estimated by a Kalman filter. The second input is the output of an accelerometer, which attempts to indicate possible physical damages to the node. The ANN ensemble is used as binary classifier, so that an output value of "1" (one) indicates that the node has no error in the measurement, and an output value of "0" (zero) identifies an error in the sensor. Both networks use Multilayer Perceptron (MLP) architecture, with four neurons in a unique hidden layer. Even though there are more state-of-the-art approaches available to perform classification nowadays, here we are trying to keep a trade-off between power consumption and fault detection accuracy, what justifies the implementation of a simpler classification method to perform pattern recognition. Fig. 2 shows a general scheme of the proposed model.

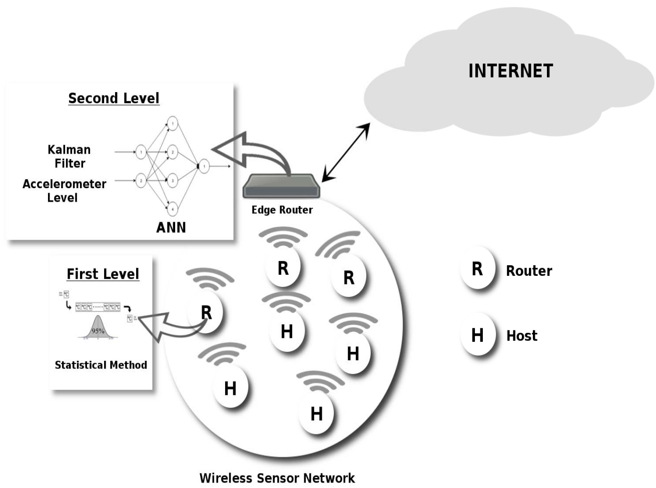

Fig. 2. General scheme of the proposed model (first and second levels).

The Kalman filter is used to track the dynamic behaviour of the system, assuming that errors in sensor measurement are common, so it contributes to reduce positive false rate in the classifier. The accelerometer measurements are used to detect possible physical damage to the node, since this is one of the major causes of hardware failure [32]. Accelerometer measurements are divided into six levels (0,1,2,3,4,6) which represent the intensity of impact. A "0" (zero) value represents no acceleration variation while a value of "6" (six) represents a large acceleration variation. The variation threshold, indicating hardware failure, was determined experimentally.

Considering that this model uses the 6LoWPAN protocol, the recovery from failure occurs through the removal of the faulty node from the *Whiteboard*. The *Whiteboard* is where the edge router stores all Internet Protocol (IP) addresses of sensor nodes [40]. But this withdrawal does not occur immediately because, when a fault is identified, the node is sent to quarantine. Thus, a fault counter is incremented and the edge router sends thirty query messages at random times to make sure the node fails. After 30 consecutive incorrect measures, it is definitely removed from the *Whiteboard*. In that case, new communication routes are created by the base station and new nodes are chosen for level 2 fault training.

IV. Practical Experiments

For the validation of the proposed fault management model, data collected from a node, participating on an actual WSN, were used in simulation. The data set consisted of a table containing the absolute differences between measured and estimated temperatures for the node and the corresponding accelerometer measurement. Table I exemplifies the database used in the simulation of the proposed model. Each accelerometer, in our model, collects acceleration data from *X*, *Y* and *Z* axes, so the integer data presented in the table represents the shake level of a node, as explained earlier in Section III.

TABLE I
Sample of the experimental database.

Kalman Filter Output	Accelerometer Level	Classification
0.099	0	0
2.241	1	1
0.605	0	0
1.170	3	1

Considering the two detection levels of the proposed fault management system, a validation experiment was also split in two parts. The first part of the experiment, to check the correct operation of the first level, was performed as follows. In the beginning, we use a data set internal to the sensor node, and we collect historical data series using the first thirty measurements. Then, we compare each of the new measures with previous results and perform the statistical, first level decisions. The results from these decisions will be evaluated using a Receiver Operating Characteristic (ROC) curve (see Fig. 3), since it is a graphical plot often used to illustrate the performance of binary classifier systems [41].

The second level detection, consisting of the ANN ensemble and responsible for identifying self and non-self operation and for recognizing normal operating and abnormal behaviour, is validated as follows. To verify the correct operation of the WSN, after training the off-line ANN, we perform validation of results through new data generated inside the network, and get the classifier decisions. These data are different from those applied in training. In the same way as it was done for the first level, the classifier results are presented by a ROC curve graphical output (see Fig. 6).

The power consumption experiment aims to compare the energy expenditure between the traditional approach on centralized fault management system and the model here proposed. At first, we implemented a system that periodically sends messages to be analysed on the base station, without previous treatment. After that, we implemented the approach presented in this work, where the exchanges are reduced by means of the statistical method proposed (first level detection). Both data are collected with independent samples and sample size bigger than 30 (thirty). The accuracy of our approach was compared with results reported by [42]. All experiments were realized in COOJA simulator using Zolertia Z1 mote, and were statistically compared as will be discussed in Section V.

V. Results and Analysis

For all experiments, we used the database as presented by Table I. For the first level fault detection experiment, an array containing the first thirty temperature measurements is initially created. In order to verify the normality of the data set, a *Kolmogorov-Smirnov* test was carried out using MATLAB ® [43], [44]. The result of this test indicated that, with a confidence level of 95.0%, we can not reject the null hypothesis. For this test, the null hypothesis indicates that "the data set comes from a Normal distribution". Table II summarizes the values found by the test.

TABLE II
Kolmogorov-Smirnov test parameters and results.

Null Hypothesis	Confidence Level	Result
Data comes from a standard Normal distribution	95.0%	0.0

As it can be seen, the data set comes from a Normal distribution, so it is possible to estimate the statistical values *mean* and *standard deviation* for this sample. Fig. 3 shows the ROC curve for the statistical classifier of the first level. When we look at Fig. 3, we can see that our binary first level classifier can be considered conservative, because the true positive rate is high and the false positive rate is low.

The confusion matrix presented in Fig. 4 confirms the results indicated by the ROC curve of Fig. 3. As it can be seen in the matrix, 96.2% of the predictions in general are correct, and 3.8% are wrong classifications. This is an expected result, since all faulty nodes were found and those ones detected as false positives should yet be evaluated by the second level detection classifier. For the second detection level, the Kalman filter outputs are shown in Fig. 5. These are used as one of the ANN inputs.

After these experiments, the classifier based on ANN ensemble achieved the results shown in Fig. 6. Through analysis of the ROC curve presented, it is possible to see that false positive rate showed values close to zero, which was very desirable and confirmed our expectations.

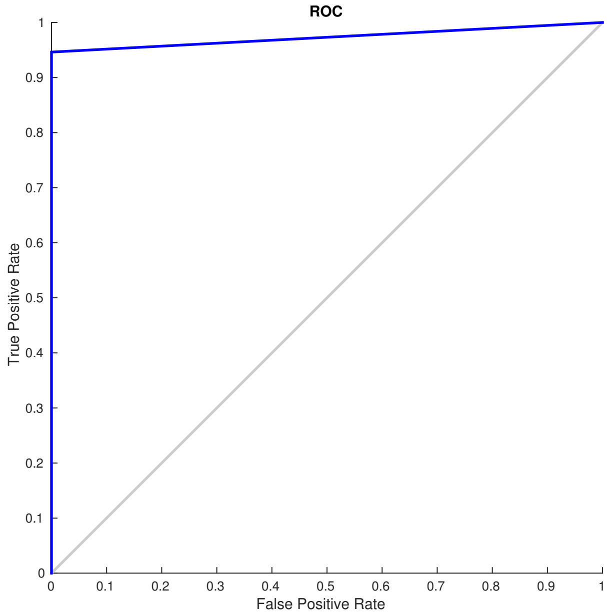

Fig. 3. ROC curve for the first level classification.

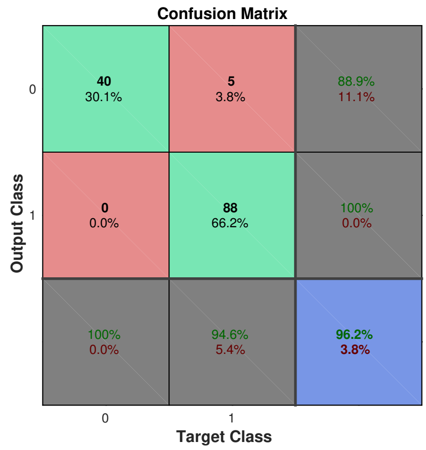

Fig. 4. Confusion matrix for the first level classification.

The confusion matrix shown in Fig. 7 indicates that the rate of false positives was 2.4%. Overall, 97.6% of the predictions were correct and all faulty nodes were detected during the experiments.

In order to compare energy consumption from both systems, here proposed and a common literature approach, we present in Fig. 8 the power involved in thirty one fault detection events. We used Analysis of Variance (ANOVA) to make sure there is statistically significant difference between the

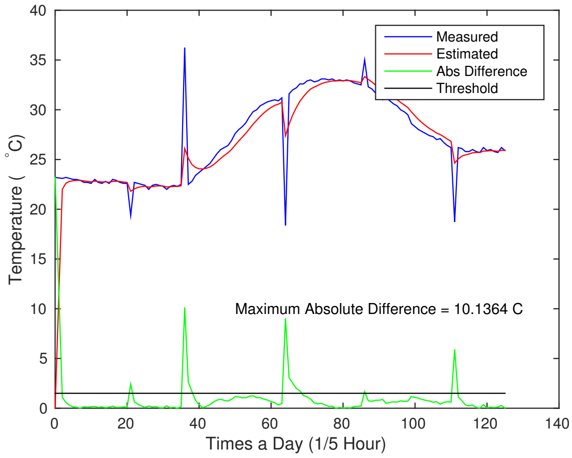

Fig. 5. Kalman Filter outputs and absolute differences.

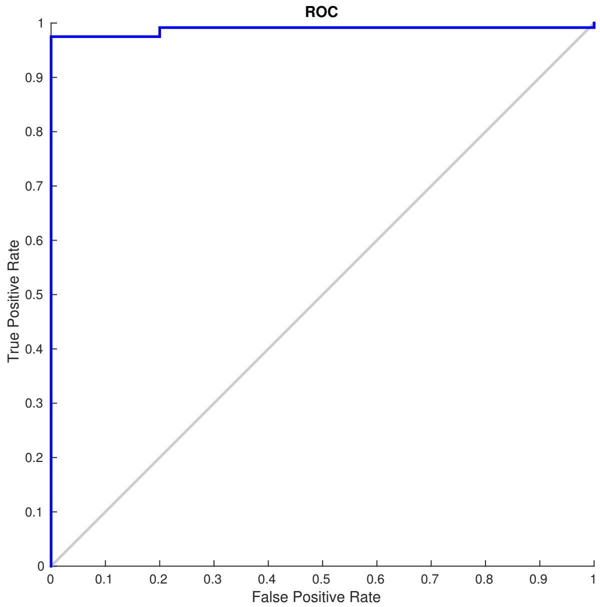

Fig. 6. ROC curve for the second level classification.

power consumption in our proposal system and another fault management system that does not use these two levels of detection fault.

In this ANOVA, the null hypothesis considered is that ”the energy consumption in both systems is the same”, and the alternative hypothesis is that ”the data are not statistically equal” and, therefore, one approach consumes more energy than the other. With 95.0% of confidence, we found a p-value of 0.0095, showing that there is a statistical difference between the power consumptions in both systems. Finally, we present in Fig. 9 the results of a Tukey test, performed to statistically

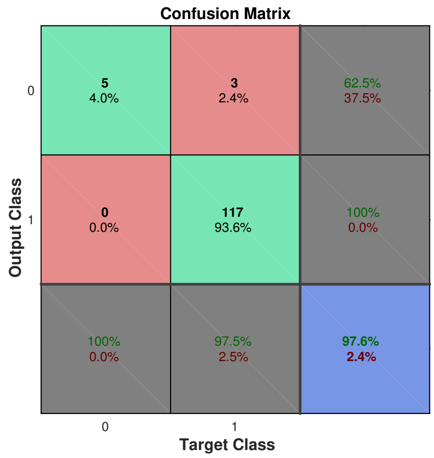

Fig. 7. Confusion matrix for the second level classification.

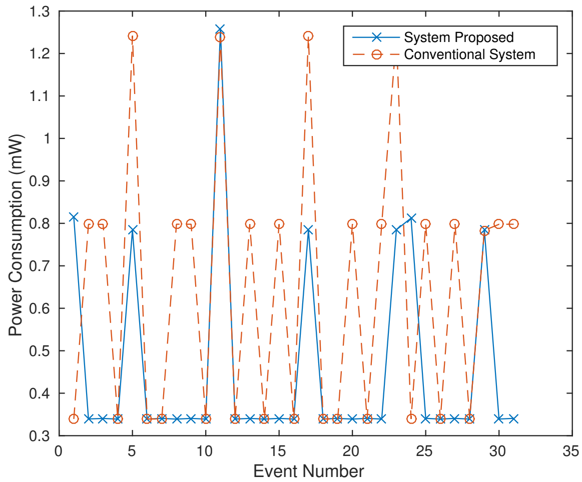

Fig. 8. Power consumption: proposed X conventional system.

confirm that the proposed system consumes, on average, 45% less energy than the common approach.

Table III summarizes some fault management approaches as well as the performance of each of them. By comparison of these values, we can see that the model presented in this work shows detection accuracy results very similar to distributed approaches, but with a reduced number of messages exchanged between the sensor nodes and the base station, which means less power consumption.

After evaluating results and statistical analysis from the undertaken experiments, it becomes clear that our centralized two-level fault detection approach shows good potential to be implemented in actual WSN. This is especially important in situations where dynamic behaviour of the measured variables and long-term drifts could mislead fault detection to erroneous classification and end up, in worst cases, with functional nodes

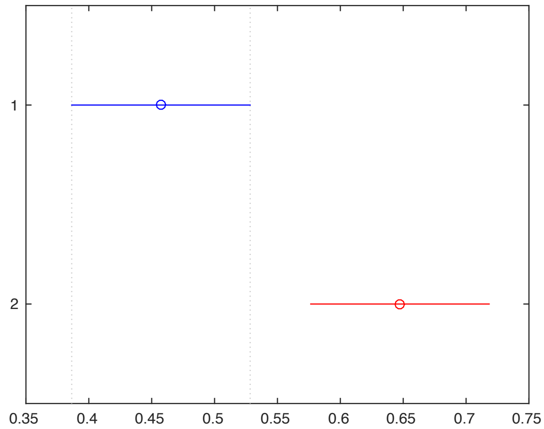

Fig. 9. Tukey test on power consumption: proposed X conventional system.

TABLE III
DETECTION ACCURACY COMPARISON BETWEEN DIFFERENT MODELS (ADAPTED FROM [42]).

Work	Year	Detection Accuracy
Nie et. Al. [45]	2012	>0.90
Ma et. Al. [46]	2012	>0.86
Kamal et Al. [47]	2013	0.88 - 0.98
This work	2017	**∼0.97**

being removed from the network and perhaps determining smaller life cycles than expected to WSN applications. Nevertheless, the reported results have yet to be confirmed with experiments undertaken with actual sensors, true messages exchanging in a limited energy harsh environment and real data being collected.

VI. Final Discussion

In the last years, WSN technology has provided better flexibility to distributed applications. Reliability on theses systems is deeply dependent on fault management systems operation and their ability to work with minimal power consumption for the maximum possible time. The results of experiments here reported showed that the proposed centralized fault management system exhibited a performance similar to other approaches cited in this paper. As of now, our system has not been fully implemented in a real environment, but our ANN classifier kept low false positive rate and all defective nodes were correctly identified, which is a hard challenge for traditional approaches. The use of a centralized fault detection approach using ANN as a binary classifier to reduce messages exchanging within the network and, consequently, minimizing power consumption, is the main contribution of this work. In the next steps of our research, we will test this approach in actual environments, and integrate this system within an Internet of Things scenario, in order to investigate possible communication bottlenecks, besides comparing it with other approaches.

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