Innovative techniques to robust wireless sensors networks

Ph.D. Booklet

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Introduction

Wireless Sensor Networks (WSNs) are distributed systems consisting of a Base Station (BS) and a number of sensor nodes. Each node is equipped with application-specific sensors, simple processing units, a wireless radio transceiver, and a power unit. These types of equipment enable the node to capture and collect data and process them, discover its neighborhood, and communicate with each other and with the BS. A wide variety of sensors that can be used in WSNs (e.g., optical-, thermal-, radar-, bio-, and acoustic sensors) make it possible to use it in applications that need extensive data acquisition, such as military application, bio-medical applications, transportation applications, environmental applications, smart appliance applications. Besides the wide range of applications, modern IoT networks can also be considered as a major evolution of WSNs[1].

However, when designing and operating of WSN, one should keep the following constraints in mind:

- Limited resources: the nodes are cheap and low quality, so they have limited memory, processing capabilities and can access narrow communication
bandwidth,

- **Limited energy**: the nodes are typically battery-operated; hence, energy becomes a scarce resource.

- **Unreliable communication**: WSN usually operated in harsh environments in terms of communications. Nodes transmit data to each other and the BS via unreliable radio channels corrupted by noise and fading.

- **Dynamic topology**: the structure of WSN changes frequently, some new nodes may be added or returned to service after a pause, and some nodes may go flat by running out of energy, failure, or malicious attack.

Despite these limitations, the performance of WSNs should satisfy some minimum level of requirements, which are known as Quality-of-Service (QoS) [2]. These QoS include reliability, energy efficiency, security, accuracy, delay and-so-forth. Lifespan is also a crucial measure of the robustness of WSNs, and researchers use several definitions of lifespan. Some of them are based on the number of alive nodes, such as that the lifespan is the time needed for $n$ number of the nodes to go flat. Other definitions are based on coverage, network connectivity, or application requirements.

Many researchers suggest various strategies and techniques that guarantee QoS and prolong the lifespan of WSN. These strategies and techniques cover almost all layers of networking protocols ranging from the physical layer to the application layer. They typically include
data reduction, protocol overhead reduction, energy-efficient routing protocols, duty cycling, topology and mobility, and energy harvesting. Some of these requirements and constraints are contradicting; the matter makes striking the right balance among them is the major challenge that faces the designers and the operators of WSN[3].

In my research, I aim to present novel solutions to improve the efficiency of WSN in terms of energy-efficient routing protocols, data reduction, and data quality. The proposed solutions include developing energy-efficient routing algorithms for deterministic WSNs, energy-efficient routing algorithms for stochastic WSNs, data reduction algorithms based on compressive sensing paradigm, and applications of WSN to Predictive Maintenance (PdM).
Chapter 1

Reliability and energy efficiency in deterministic WSN

1.1 Problem statement and objectives

The energy efficiency of WSN is not only concerned with the amount of consumed energy, but also it is essential to guarantee uniform energy distribution among the nodes. The lack of load balancing may cause the early death of some nodes, which then breaks the connectivity of WSNs and eventually reduces the life span. Energy efficiency is also essential from the point of reliability. Information packets may reach the BS with a given probability, and reliable communication requires
that this probability should exceed a pre-defined threshold. Most protocols (LEACH, PEDAP, PEGASIS) use techniques such as clustering and chaining to achieve energy efficiency by enforcing uniform energy distribution and maximum longevity, but they do not provide reliable links, whereas the lost data means wasted energy. Besides that, such protocols and their modification use methods like round-robin and assessing the remaining energy for the selection of cluster heads and chain leaders. However, they do not provide a clear and authoritative measure for the uniformity of energy distribution and load balancing; the absence of such measure may cause unsuccessful selection for the cluster heads or the chain leaders, where themselves become bottlenecks of the WSN.

A lot of researches as [4, 5, 6] improves reliability either by providing more redundant data, which further increases energy consumption, or by providing alternative links and backup devices, which, on the other hand, increases the cost and is not incoherent with the limited capacity of nodes. Such a contradiction between energy efficiency and reliability makes it imperative to look for novel solutions that strike an optimal balance between them.

My objective in the area of reliability and energy efficiency is to develop new algorithms for WSNs that can maximize network longevity (achieve maximum throughput) under the constraint of reliable communication. The proposed algorithms also select the optimal path that guarantees a uniform energy distribution based on a clear and proven measure. They can be used in WSN
and any routing-based systems such as telecommunication and transportation. They can also be used in systems that need load balance (such as resource management systems).

1.2 Maximization of the Minimum Residual Energy protocol (MM-REP)

In this research, I used the Rayleigh fading model [7]. In this model to achieve $P_{ij}$ probability of successful packet transfer from node $i$ to node $j$ over the distance $d_{ij}$ requires transmitting energy $g_{ij}$ given by the formula

$$g_{ij} = -d_{ij}^\alpha \frac{\theta \sigma_Z^2}{\ln(P_{ij})}$$ (1.1)

where $\theta$ is the so-called modulation and coding constant [8], $\sigma_Z^2$ denotes the power of noise, $\alpha$ is the large-scale path loss exponent (usually $2 \leq \alpha \leq 6$).

The reliability constraint is expressed by a pre-defined data loss percentage $\varepsilon$; where the probability of overall success of packet transmission from the source node to the BS is supposed to fulfil

$$\prod_{j=0}^{m} P_{ij}^{l_{j+1}} = 1 - \varepsilon.$$

The energy of the network at time instant $k$ is described by an energy state vector $\mathbf{c}(k) = (c_1(k), ..., c_N(k))$ where $c_i(k)$ represents the available battery power at node $i$ at time instant $k$. We assume that all the nodes have the same initial energy at time instant 0, i.e. $c_i(0) =$
The optimal path is selected if over which a packet is sent to the BS and the minimum remaining energy is maximum subject to the constraint that the packet will reach the BS with a given probability.

Thus, the path over which the packet is forwarded to the BS (denoted by $ℜ$) is optimal if

$$ℜ : \max_{ℜ} \min_{i} c_i(k + 1)$$

subject to the constraint $\prod_{j=0}^{m} P_{lj_{j+1}} = 1 - \varepsilon$.

I assume that packets are forwarded to BS via an m-hop path and the sender node is node $l_0 = s$ and the sink node is the BS denoted by $BS = m + 1$. The path containing the sender and the relay nodes is denoted by $ℜ = \{l_0, ..., l_m\}$. So, there are $m + 1$ components changing in vector $c(k + l)$ compared to $c(k)$, given as $c_l(k + 1) = c_l(k) - g_{l_{j},l_{j+1}}, j = 0, ..., m$. If one wants to ensure that the packet sent by node $s$ reaches the BS with a given probability $(1 - \varepsilon)$, then the reliability constraint can be expressed as $\prod_{j=0}^{m} P_{lj_{j+1}} = 1 - \varepsilon$.

Thus, in the case of m-hop routing, one has to solve the following constrained optimization problem:

$$l_{1\text{opt}}, l_{2\text{opt}}, ..., l_{m-\text{opt}} : \max_{l_{2},l_{3},...,l_{m}} \min_{j \in 0, ..., m} (c_{l_{j}}(k) - (g_{l_{j},l_{j+1}})).$$

subject to the constraint $\prod_{j=0}^{m} P_{lj_{j+1}} = 1 - \varepsilon$.

The minimum residual energy will be maximum if
the residual energy at all the relay nodes are equal to each other $c_{l_j}(k+1) = c_{l_{j+1}}(k+1)$, $j = 0, ..., m$. So

$$c_{l_j}(k) - g_{l_{j},l_{j+1}} = c_{l_{j+1}}(k) - g_{l_{j+1},l_{j+2}}.$$  (1.4)

The $m + 1$ equations above yield a solution to $g_{opt} = (g_{l_0l_1,opt}, ..., g_{l_mBS,opt})$. One can calculate $g_{opt}$ for all possible $m$ hops paths fixing the path $\mathcal{R} = \{l_0, ..., l_L\}$, where $L$ is the actual number of hops. Then the optimal path $\mathcal{R}_{opt} = \{l_0, l_{1,opt}, ..., l_{m,opt}\}$ can be sought by solving the following problem:

$$\mathcal{R}_{opt} = \{l_0, l_{1,opt}, ..., l_{m,opt}\} : \max_{\mathcal{R}} c_{l_0}(k) - g_{l_0l_1, opt}. \ (1.5)$$

### 1.3 Optimal path selection based on the network energy entropy

I use an entropy-like measure to evaluate the residual energy distribution. Based on that, I propose a routing algorithm that will maximize this entropy, thus ensuring that the residual energy distribution falls close to uniform.

One can define the entropy of the normalized residual energy distribution on the nodes of the network $\mathcal{R} (k) = c_1(k), c_2(k), ..., c_N(k)$ at time instant $k$ as follows

$$H(\mathcal{R}) = \sum_{i=1}^{N} \frac{c_i(k)}{\sum_{j=1}^{N} c_j(k)} \log \frac{\sum_{j=1}^{N} c_j(k)}{c_i(k)}. \ (1.6)$$

In order to enforce energy balancing we choose paths which will decrease the entropy the smallest possible
way. The change of the entropy is calculated as thus, the change of the entropy is

$$\Delta \mathcal{H} = \nabla H(\bar{c})^T \star \Delta \bar{c}(k).$$

(1.7)

where $V$ is the gradient of the entropy, and $\Delta c_i$ is: $c_i(t + 1) - c_i(t)$ and $c_i(t + 1)$ is calculated based on Rayleigh fading model Eq. (1.1) to guarantee the balance between energy efficiency and reliability as follows:

$$c_{ij}(t + 1) = c_{ij}(t) - \left( -d_{ij} \frac{\Theta \sigma^2 Z}{\ln(P_{ij})} \right)$$

(1.8)

The optimal path is the one that keeps this gradient minimum, thus, enforcing only small changes in the network energy entropy, guaranteeing that the energy distribution falls as close to uniform as possible. In this way, all nodes will go flat more or less at the same time. The optimum choice of relay nodes (the optimal path) which minimizes the change in the gradient can be obtained as

$$l_{opt} = \min(\Delta \mathcal{H}).$$

(1.9)

**Thesis one:**

- I presented a method for selecting the relay nodes based on the remaining energy and reliability.

- I proposed MMREP to select the path that maximizes the remaining energy of its nodes subject to the reliability constraint.

- I introduced the entropy-like function to measure
the uniformity of residual energy distribution.

- I proposed OREBP, which selects the path based on the entropy of residual energy of the path.

1.4 Numerical results

The performance of the proposed algorithms MM-REP and OREBP, respectively, is evaluated and compared to the PEGASIS protocol. In PEGASIS, each node forwards the packet to its closest neighbor; when the packet arrives at the chain leader, it sends the packet directly to the base station.

Figure 1.1 shows the residual energy of the nodes of the chain for MMREP, OREBP, and PEGASIS, respectively, when the first node goes flat. In MMREP and OREBP, we note that almost all the nodes have the same residual energy level; the residual energy is distributed more uniformly (near zero) for all nodes. In PEGASIS, we note that as the node gets further away from the BS, it loses energy at a higher rate; the residual energy of the nodes decreases as the nodes get farther from the BS. So, we note the uneven distribution of the residual energy.
Figure 1.2 shows the life span of a network which uses MMREP, OREBP, PEGASIS, subject to a reliability constraint, with different data loss percentage $\varepsilon$ values, 0.025, 0.05, 0.075, 0.01, 0.125 and 0.15, respectively. Since PEGASIS does not consider reliability as a QoS parameter when calculating transmission energy; the figure shows that it has a higher life span than MMREP and OREBP; it uses lower transmission energy, which causes a higher packet loss percentage, which means lower reliability; hence, the life span of a network with PEGASIS is the same regardless of data loss percentage $\varepsilon$. However, in the case of the proposed algorithms, life span increases with increasing data loss percentage $\varepsilon$, while the probability of successful packet transmission $(1 - \varepsilon)$ decreases. With MMREP and OREBP, the life span is a function of $\gamma$. The users can trade-off between the reliability represented by $\gamma$ and the life span.
Figure 1.2: Lifespan with different data loss ($\varepsilon$).

Figure 1.3 shows the success probability with OREBP and PEGASIS. We assume a predefined data loss rate ($\varepsilon = 0.05$) for OREBP. The success probability for PEGASIS is calculated as mentioned above. The figure shows the success probability against a variable number of hops ranging from one to six. OREBP always has a higher success probability than PEGASIS, although the value depends on the number of hops. The figure shows that using OREBP improves the reliability from 63% in a one-hop path to 71% in the case of a six-hop path. Lost data means wasted energy. The figure shows that the success probability decreases with an increasing number of hops. In OREBP, we can control the success probability by trading off between pre-defined data loss with life span, as shown in Fig. 1.2.
Figure 1.3: Success probability when data loss ($\varepsilon = 0.05$).
Chapter 2

A new energy-efficient and reliable protocol for stochastic WSNs

2.1 Problem statement and objectives

In stochastic WSN (where the packets are generated and transmitted subject to queuing dynamics) may also be known as queuing WSNs, the MAC of the device builds queues in a buffer where the data is held prior to transmission.

My research aims to build new algorithms based on the backpressure principle, where the movement of the packets among the nodes depends mainly on the backlog difference of the nodes. The proposed algorithm uses the backpressure principle in a way that provides
a good balance among QoS requirements of WSN; reliability, energy efficiency, throughput, and delay. Thus, it should reduce the concerns about the appearance of some phenomena associated with stochastic WSN, such as end-to-end delay and low reliability due to overflowing and congestion. Furthermore, energy efficiency should be maintained in both dimensions; the amount and the distribution.

### 2.2 Reliable and energy-efficient stochastic routing

The backpressure algorithm was introduced in [9], and it deals with both routing and scheduling (forwarding) processes. In the routing process, the most effective path is found, while in the scheduling process, the decision to activate the proposed route is taken. At time slot $t$, the backpressure algorithm calculates the weight of all possible outgoing links; it defines the link with maximum weight at time slot $t$ as:

$$\omega_{i,j}(t) = \max(\Delta Q_{i,j} - K \theta_{i,j}) \quad (2.1)$$

where $\Delta Q_{i,j}$ is the differential backlog for both ends of the link, $\theta_{i,j}$ is the cost function, and $K$ is a constant used to normalize the cost function, the tie is broken arbitrarily.

The link with maximum weight is activated under
schedule $\pi(t)$ based on the following optimization function:

$$\pi(t) = \arg \max_{\pi \in l} (\omega_{i,j}(t)\bar{r}_{i,j}) \quad (2.2)$$

where $r_{i,j}$ is the expected link rate and $l$ is the set of all feasible schedules subject to link interference model, and $\omega_{i,j} > 0$ [10, 11]

In my work, I extended the cost function of the back-pressure algorithm with a term measuring the uniformity of the distribution of the residual energies of the nodes. I used an entropy-like measure on the energy distribution, by which we can measure the uniformity of residual energy distribution. At instant $t = 0$, all the nodes have the same residual energy level, so the entropy is maximum. To keep it as high as possible, then the change of the entropy should be as minimum as possible as explained in section (1.3) and Eqs.(1.6-1.8).

I proposed the so-called BackpPressure energy Entropy Based Protocol (BPEEBP) algorithm, where the weight of the link depends on the differential backlog for both ends of the link, and the change of the entropy of residual energy of the chain. The cost function $\theta_{i,j}$ in 2.1 will be the change of the entropy $\Delta \mathcal{H}$, the weight of the link increases as the differential backlog increases and the change of the entropy decreases, thus equation (2.1) becomes:

$$\omega_{i,j}(t) = \max(\Delta Q_{i,j} - K \cdot \Delta \mathcal{H}_{i,j}) \quad (2.3)$$

then, the link satisfies equation 2.2 is activated.

**Thesis two:**
• I proposed BPEEBP, a routing algorithm for stochastic WSNs; it based on four significant principles; On-OFF scheme to provide energy-efficiency, back-pressure principle to control the traffic load balance, entropy of residual energy to control the uniform distribution of residual energy, and Rayleigh fading model is to guarantee the balance between consumed energy and reliability.

2.3 Simulation and performance evaluation

I evaluated the performance of the proposed algorithm by comparing it with the traditional backpressure. I used Matlab and Simulink (simevents) to model and simulate our system; each simulation lasted for 1000 units of time. The simulated network consists of 100 symmetrical nodes deployed randomly onto a grid of 100X100 according to the 2D normal distribution; the base station is selected randomly, and the Dijkstra shortest path algorithm forms a set of short paths.

I used the variance of the consumed energy to express its uniformity. Figure 2.1 shows the variance of consumed energy in different chain lengths (i.e., different number of nodes included in the path), 5, 6, 7, 8, and 9. It shows that BPEEBP has a lower variance than traditional backpressure for all lengths of the chains (5,6,7,8,9). Figure 2.2 shows the total consumed energy by the nodes during the simulation period. One can
note that all the nodes consumed less energy when using BPEEBP in about 9%.

\textbf{Figure 2.1: The variance of consumed energy vs length of the chain}

\textbf{Figure 2.2: Total consumed energy vs length of the chain}

Figure 2.3 shows that we still have a high packet delivery rate (throughput), there is about 16% enhancement in comparison with traditional pack-pressure by using BPEEBP. The figure shows the relation between the packet arrival rate at the base station and packet generation rate at the nodes.
Figure 2.4 shows that in the case of BPEEBP, better uniformity in the distribution of consumed energy and better load balance among the nodes yields a longer lifespan. We studied the lifespan in the case of the traditional backpressure algorithm and BPEEBP regarding
different utilization values $\rho(0.1 - 0.9)$; the figure shows that we have a significantly longer lifespan for all tested cases in about 50% on average.
Chapter 3

Reliable and energy-efficient algorithm based on data reduction

3.1 Problem statement and objectives

Data reduction techniques are effective tools used to improve energy efficiency, reliability, and memory usage in the shadow of limited resources of the nodes. Recently, many researchers propose a compressive sensing paradigm as a compression tool, where the base station can reconstruct the transmitted data from very few samples in case of sparse data, which can be obtained by expansion of the dense data on an orthonormal basis.
Compression of data may cause low reliability because the BS may not be able to reconstruct the original data correctly and accurately, which is known as reconstruction error [14]. The probability of the reconstruction error depends on the number of samples, but increasing the number of samples needs more energy. In comparison, less samples means less energy but higher reconstruction error probability. Therefore, to achieve optimal energy efficiency and optimal reliability (a function of reconstruction error), we need to find the best trade-off between energy efficiency and reconstruction error.

My goal was to develop a CS-based chain routing algorithm; it gives the user a chance to bias towards a specific party of balance equation between energy efficiency and reliability. Furthermore, the algorithm helps to construct the WSN in a way that aids the user in achieving his choices. In addition to the WSN application, the developed algorithm can be used as a heuristic optimization algorithm to balance between contradiction factors; it can be used to structure the graph-based application and optimal resource distribution map.

3.2 Compressive sensing in WSNs

If $\theta$ is a dense vector represents the original signal, then it can be expanded into an orthonormal basis $\Psi$ (such as wavelet basis, Fourier basis, DCT, etc.) to acquire a sparse vector $x$ as follows:
\[ x = \Psi \theta, \Psi \in R^{N \times N}, \theta \in R^N. \] (3.1)

\( x \) is then a sparse vector with length \( N \) and its \( K \) significant elements is sampled into vector \( y \) as follows:

\[ y = \Phi x, y \in R^M, \Phi \in R^{M \times N} \] (3.2)

where \( \Phi \) is the sensing matrix (measurement matrix) and \( M \) is the number of measurements (samples) and \( N \gg M \).

In compressive sensing to reconstruct \( x \) correctly from \( y \), \( \Phi \) should obey these two conditions:

- The coherence (\( \mu \)) between \( \Psi \) and \( \Phi \) should be as minimum as possible where:

\[ \mu(\Phi, \Psi) = \sqrt{N} \max_{1 \leq j \leq M} \max_{1 \leq i \leq N} | \langle \varphi_j, \psi_i \rangle | \] (3.3)

The upper bound of \( \mu \) is one, where the lower bound is a function of \( M \) and \( N : \) \( \sqrt{\frac{N-M}{M(N-1)}} \)

- It satisfies the restricted isometry property (RIP) of order \( K \), which is achieved if the restricted isometry constant \( (RIC)\delta_k \) is not close to one, where:

Since \( N \gg M \), There are infinitely many possible solutions nad each solution represents a possible signal reconstruction, if the RIP holds, \( l_0 \)-norm and \( l_1 \)-norm can be used to reconstruct the signal if \( \hat{x} \) is the reconstructed vector:
\[ \hat{x} = \arg\min_{y = \Phi x} \| x \|_0 \]  
\[ \hat{x} = \arg\min_{y = \Phi x} \| x \|_1 \]  

Reconstruction by \( l_0 \)-norm is accurate, but it is slow because it is an NP-complete algorithm, where \( l_1 \)-norm leads to a linear programming problem \([15]\).

### 3.3 MOGA in WSNs.

I developed a multi-objective genetic algorithm (MOGA) that seeks the optimal number of measurements (\( M_{opt} \)), the optimal transmission range (\( R_{opt} \)) (that guarantees the graph connectivity), and the optimal measurement matrix (\( \Phi_{opt} \)), based on fitness functions of:

1. Energy efficiency where:
   \[
   E = M \left( n_c \left( \frac{R^2}{2} \right)^{\alpha/2} + \left( \frac{D^2}{6} \right)^{\alpha/2} \right) \]  
   \[ (3.6) \]

2. Reconstruction error where:
   \[
   e_y = \frac{1}{M} \| y - \hat{y} \|_2^2 \]  
   \[ (3.7) \]

3. Coherence of sensing matrix as in Eq.(3.3)

where \( E \) is the energy, \( M \) is the number of samples, \( R \) is transmission range, \( n_c \) is the average path length, \( \alpha \) is the path-loss exponent, \( D \) is the dimension of the sensing.
field, $\mu$ is the coherency of sensing matrix and $\delta$ is the restricted isometry constant ($RIC$), $K$ is the sparsity level, and $N$ is the number of nodes.

### 3.4 CCS-MOGA

The output of MOGA is the optimal measuring matrix with minimum mutual coherence and a Pareto front, as shown in Fig. 3.1. The figure demonstrates that as the energy increases, the reconstruction error decreases and vice versa.

Based on the calculated $M_{opt}$ and $R_{opt}$, WSN is divided into $M$ paths, as follows:

1. Selecting $M$ leaf nodes $(cl)$ that satisfy:

$$m \in cl \equiv \max_{\forall m \in N} \left\{ \min_{\forall i \in cl} \text{dis}(m, i) \right\}$$

\[ (3.8) \]
2. $M$ paths are constructed; each of them starts with a leaf node as a header, then in turn, each leaf node select the closest node within $R_{opt}$ to be a member of it’s path, the new members be the new header, and so on.

3. Rearrangement the nodes in the path to form a shortest path which is $spath_i = \{cl_i, cl_i + 1, \ldots, BS\}$ where:

$$spath_i = \min_{path_i} \sum_{j=1}^{j=n_c-1} dis(j, j+1) \quad (3.9)$$

At the beginning of a transmission round, each path selects a path leader based on the ratio of residual energy and distance from the sink. Each node receives the data from the preceding node and add it to its data, and pass the summation to the next node in the path, $x_i = \sum_{i=1,2,\ldots,n_c} x_i$, $i = \{1, 2, \ldots, n_c\}$, and $n_c$ is the length of the path.

$CL$ arranges the received data into $X_m \in R^{1*N}$; it includes the readings of each node into its corresponding element of $X_m$, $X_m$ is a sparse vector, all its elements are zeros, just the elements corresponding to members of path $m$, The sparsity level $K$ is determined by the number of measurements, fewer number of measurements mean longer paths and lower level of sparsity. $CL$ calculates $y_m = \phi_m X_m$, $m = \{1, 2, \ldots, M_{opt}\}$ and transmits it directly to the BS. BS concatenates $y_m, m = \{1, 2, \ldots, M_{opt}\}$ to obtain $Y \in R^{1*M}$ which reconstructed to recover $X$, $X = \bigcup_{m=1}^{M} X_m$. Proposed
CS model is demonstrated in Fig. Proposed CS model is demonstrated in Fig. 3.2.

![Compressive sensing model](image)

*Figure 3.2: Compressive sensing model.*

**Thesis three:**

- I proposed a multiple objectives genetic algorithm to strike the right balance between the energy efficiency and reconstruction error of the compressive sensing method.

- I applied a genetic algorithm with appropriate parameters to improve the characteristics of the sensing matrix by reducing its mutual coherence.

- I presented a greedy algorithm to split the WSN into multiple paths based on the above optimization algorithms.
3.5 Simulation and Numerical results

I used MATLAB R2018 to simulate the algorithm. I compared the non-compression, proposed plain compression, and some other plain compression algorithms with each other. Also, we evaluated the impact of optimization on the system performance concerning energy efficiency and accuracy of reconstruction.

I assumed different numbers of sensors (25-500 nodes) deployed in a grid of 100x100m; the nodes are deployed according to a 2D normal distribution. I presume MICA2, where ETx is 3.12 µJ/bit, and ERx is 2.34 µJ/bit [16], the energy spent by the electronics is neglected and α is 2.5 for both short and long transmissions.

![Observed Data error](image)

Figure 3.3: Reconstruction error of optimal Φ and random Φ.

Figure 3.3 emphasizes that the optimization of the
sensing matrix in terms of mutual coherence allows mostly lower reconstruction error regardless of the number of measurements. A random matrix may show a low coherence in some rare cases because of the nature of its randomness. However, we still need systematic optimization, as coincidences should not control our systems.

Figure 3.4 shows the relations between the number of measurements as an optimization variable on one side, and the objectives of the optimization from the other side. The left y-axis shows the energy as an objective, where the right y-axis shows the reconstruction error as the second objective.

![Figure 3.4: The relation among Energy, error and number of measurements of WSN consists of 500 nodes.](image)

The result coincides with the theoretical depiction mentioned above; as the number of measurements increases, more energy is consumed, but less error probability transpires. The crossing point between the two curves matches the knee point of the Pareto front shown in Fig. 3.1.
Figure 3.5 shows the energy efficiency characterized by the average of consumed energy per node after 1000 transmission rounds. Although the figure shows a much lower energy consumption of CCS-MOGA, it is a reasonable result because each CL sends just one element of vector $y$ as shown in 3.2, wherein the case of non-CS, each CL sends a vector of 100 elements. We note that the average of consumed energy per node in the case of T-CS changes linearly with the size of the network because the length of vector sent by CL depends on $M$, as $M$ increases the length of the vector increases and the spent energy increases too.

Figure 3.5: The average consumed energy per node.

Figure 3.6 shows the variance of the consumed energy of the nodes. Low variance means more uniformity of distribution of consumed energy. WSNs use CS-MOGA show a very low variance, so they tend to have a longer life span than the other two scenarios.
Figure 3.6: The variance of the consumed energy.
Chapter 4

Predictive Maintenance system for WSNs

Predictive Maintenance (PdM) is concerned with collecting data and estimating the operability of the system under observation. Thus, PdMs maximizes the system life cycle, minimizes unplanned downtime, and improves the reliability and production quality; it also reduces the cost of maintenance significantly. To achieve these objectives, it is essential to develop efficient data collection methods and powerful techniques to predict the performance of the system in the future and estimate the remaining time to failure.

Researchers use neural networks and machine learning techniques to predict the performance of WSN to improve reliability [17], energy efficiency, or the efficiency of network intrusion detection [18]. There is a real need
to adopt the principles of PdM to monitoring the operational conditions of the WSN and estimates the functional status of the network. (”OK” or faulty)

PdMs of WSNs should have low complexity to be incoherent with the limited resources of WSNs in terms of energy, memory, processing capacity..., etc.

My goal is to develop a PdM to estimate the probability that the monitored system is still fully operational in the next $M$ steps for WSNs. The input features are the previous $K$ observations of the QoS parameters in the network, including energy efficiency, throughput, reliability, and delay. The output is a vector of length $M$ that represents the probability of operability status of WSN after $M$ steps; I also aim to make the proposed PdM compatible with limited resources of WSN by using quantization and encoding schemes.

\section{Predicting the forward probability distribution by FFNN}

If $x(k)$ is a time series summarizing the information about the monitored system, I assume that if $x(k) > A$, then the system is malfunctioning and urgent maintenance action is required; otherwise, the system operates normally. if the probability that the system will stay normal for the next $M$ is $(1 − \varepsilon)$, then :

$$M : P(x^+(k) \in A|x^-(k) = (i, ..., j)) \geq 1 − \varepsilon \quad (4.1)$$
where:
\[
\begin{align*}
\mathbf{x}^+(k) &:= (x(k + M), x(k + M - 1), \ldots, x(k)) \\
\mathbf{x}^-(k) &:= (x(k - 1), \ldots, x(k - K + 1))
\end{align*}
\] (4.2)

one can write this probability in a more compact form:
\[
M : P(\mathbf{x}^+(k) \in B|\mathbf{x}^-(k) = (i, \ldots, j)) \geq 1 - \epsilon 
\] (4.3)

where set B is defined as: \( B := \{ \mathbf{x} : x_i < A, \ldots, x_M < A \ \forall \ 1 \leq i \leq M \} \)

Introducing the following two vectors
\[
\begin{align*}
\mathbf{s}^{(1)} &= (s_1^{(1)}, s_2^{(1)}) = (1, 0) \rightarrow \text{ha } \mathbf{x}^+ \in B \\
\mathbf{s}^{(2)} &= (s_1^{(2)}, s_2^{(2)}) = (0, 1) \rightarrow \text{ha } \mathbf{x}^+ \notin B
\end{align*}
\] (4.4)

one can form a training set
\[
\mathcal{T}^{(K)} = \{ (\mathbf{x}^-(k), s(k)), k = 1, \ldots, K \}, s(k) \in \{ s^{(1)}, s^{(2)} \}
\] (4.5)

A feed-forward neural network can be trained to predict the future status of the system based on the previous K observation as follows:
\[
E(s|\mathbf{x}^-) = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} P(\mathbf{x}^+ \in B|\mathbf{x}^-) \\ P(\mathbf{x}^+ \in B^c|\mathbf{x}^-) \end{pmatrix}
\] (4.6)

where:
\[
\begin{align*}
E_1(s|\mathbf{x}^-) &= P(\mathbf{x}^+ \in B|\mathbf{x}^-) \\
E_2(s|\mathbf{x}^-) &= P(\mathbf{x}^+ \in B^c|\mathbf{x}^-)
\end{align*}
\] (4.7)
4.2 PdM for WSNs – quantization and sparsity

The limited resources of WSNs requires a low complexity PdM, to reduce the complexity I use:

1. Lloyd-Max quantization algorithm: it is selected because the distribution of observations is not uniform, Lloyd-Max quantization algorithm takes the PDF of samples distribution on account to minimize the mean square quantization error $\sigma$. Finding the optimal quantized level $q_i$ of sample $r$ is an iterative process where:

$$q_i(r) = \frac{\int_{c_i}^{c_{i+1}} r \cdot f(r) \, dr}{\int_{c_i}^{c_{i+1}} f(r) \, dr}$$

(4.8)

where $c_i$ and $c_{i+1}$ are the regions of the proposed quantization level $q_i$, and $f(r)$ is the PDF of the samples, the goal is the minimization of quantization error ($\sigma$), which is:

$$\sigma_q^2 = \sum_{i=1}^{Q} \int_{c_i}^{c_{i+1}} (r - q_i)^2 \cdot f(r) \, dr$$

(4.9)

where $Q$ is the numbers of the quantization levels.

2. straightforward encoding scheme, it is compatible and complementary with the quantization algorithm, each quantization level is encoded into an orthonormal vector set:
\[ q_l \rightarrow s q_l : sq_l(i) = \begin{cases} 1 & \text{if } i = l \\ 0 & \text{otherwise} \end{cases}, i = \{1, 2, \ldots, Q\} \]

## 4.3 Dataset for training

The dataset used for training, validation, and testing is imported from [19]. The researchers collected the data experimentally as described in their paper [20]. I collected 10000 entries. Each entry summarizes the average measured parameters of 300 packets; I fixed the power transmission level at -19 dBm and change the other pre-configured parameters for the possible combination. Both, pre-configured and measured parameters are used to calculate the QoS requirements needed for training; reliability, energy efficiency, throughput and delay.

QoS metrics are contradictory; improving reliability decreases energy efficiency, and improving energy efficiency reduces throughput, and so on; the user should trade-off among these metrics. To define the operational status of the WSN, I define a range of each metric as follows:

\[
\begin{align*}
\alpha^+ & \leq PER < \alpha^- \\
\beta^+ & \leq En < \beta^- \\
\gamma^+ & \leq Tp < \gamma^- \\
\delta^+ & \leq \rho < \delta^- 
\end{align*}
\]

If the four metrics are within the specified range, then
the operational state of WSN is “OK” corresponding to $s^{(1)} = (1, 0)$ as defined in Eq. (4.6), which means that no maintenance is needed; otherwise, the operational statue is “NOK” corresponding to $s^{(2)} = (0, 1)$ as defined in Eq. (4.6).

**Thesis four:**

- I proposed a prediction model that estimates the forward probability distribution of the operational status of the monitored system in the next $M$ future steps based on previous $K$ readings of QoS parameters.

- I implemented the proposed prediction model by FFNN model.

- I presented a mathematical analysis for configured, measured, and calculated QoS parameters of WSNs.

- I applied the proposed model as PdMs for WSN; it predicts the needing of WSN for maintenance after $M$ steps, the prediction is based on previous $K$ observations of QoS requirements.

- I introduced quantization and encoding schemes to make the proposed model compatible with limited resource WSNs.

### 4.4 Numerical results

First, I investigated the effect of quantization and encoding on the accuracy and complexity of the PdM system. Figure 4.1 shows the complexity of the algorithm
under different numbers of hidden layers; it demonstrates that the algorithm uses quantized and encoded data that has lower complexity than the one that uses the raw data, regardless of the number of hidden layers. Both algorithms show an ascending tone of training time as the number of hidden increases.

![Complexity of original data vs quantized and encoded data](image)

*Figure 4.1: Complexity of original data vs quantized and encoded data*

The irregularity noticed in both curves is justified by the randomness of initial values of the training process’s weight and biases.

In Fig. 4.2, one notices that the raw (original) data show better accuracy than the quantized and encoded data; this happens because, besides the prediction error, there is a quantization error calculated by Eq.4.9. The algorithm uses the raw data exhibits better accuracy as the number of hidden layers increases; with quantized and encoded data, the input data appear as a lookup table, so one notices the low variance of accuracy with quantized and encoded data regardless of the number of
the hidden layers.

Figure 4.2: Accuracy of original data vs quantized and encoded data

Figure 4.3 shows the performance of the model under different values of $M = (1 - 10)$, where the number of hidden layers is set to ten layers, and the number of previous observations is set to 3. The left y-axis characterizes the $MSE$, where the right y-axis characterizes the execution time. The figure shows that as $M$ increases, both the execution time and the $MSE$ increase, because longer output vector should be estimated. That the system will be faulty after five operational steps, and maintenance should take place.
Figure 4.3: The relation among MSE, Execution time, and $M$.

Figure 4.4 demonstrates the effect of the number of previous observations $k$ on $MSE$ and execution time. The number of the hidden layer is set to ten, and $M$ is set to 5. The left y-axis represents the $MSE$, and the right y-axis represents the execution time; a large $k$ means less $MSE$ but a longer execution time.

Figure 4.4: The relation among $MSE$, Execution time, and $K$. 

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Summary and conclusions

In this dissertation, I proposed some innovative techniques for designing robust WSNs for optimal energy efficiency, reliability, and longevity. I introduced new algorithms MMREP (Maximum of the Minimum Residual Energy Protocol) and OREBP (Optimal Residual Energy Based Protocol) to maximize the minimum remaining energy and achieve uniform energy consumption subject to a predefined reliability constraint. The proposed protocols improve the energy efficiency in terms of the life span, the amount and the distribution of the consumed energy. I also proposed a new algorithm BPEEBP (BackPressure and Energy-Entropy-based Protocol) for stochastic WSNs. It controls the distribution of the traffic and the residual energy subject to a predefined reliability constraint. It shows better performance regarding energy efficiency, E2E delay, and throughput. The proposed algorithms can be used in WSNs and in any routing-based systems such as telecommunication, transportation; they can also be used in systems which
need load balance, such as resources management systems.

I developed a new optimization method CCS-MOGA (Chained Compressive Sinssing based on Multiple Objects Genetic Algorithm) to find the optimal values of the variables of the compressive sensing paradigm. I optimized the number of measurements, transmission range, and the mutual coherence of the sensing matrix. CCS-MOGA maximizes the energy efficiency and minimizes the probability of reconstruction error. It also provides a dynamic construction of WSN based on the values of optimization variables and objectives. In addition to WSN, the developed algorithm can be used as a heuristic optimization algorithm to strike the right balance between contradicting criteria of networking. The new method can be used in the structure of the graph-based application and optimal resource distribution map.

I used the FFNN machine learning model to build a PdM system for WSN; it predicts the operational status ("OK" or faulty) after $M$ time steps based on $K$ previous readings of QoS requirements of the WSN. I used the real estate data set of a one-hop WSN. I also used quantization and encoding schemes to make the system incoherent with the limited resources of the WSN. I revealed that the complexity of systems is improved by quantization, encoding, small $M$, and small $K$. The accuracy is improved by using the raw (original data), small $M$, and large $K$.

In this way, my research has contributed to industrial and IoT data acquisition which may help intelligent system monitoring. The proposed algorithms can
be used as efficient data collection for AI based system supervision. They had several applications ranging from surveillance systems to Industry 4.0.
Bibliography


[16] Haojun Teng, Kuan Zhang, Mianxiong Dong, Kaoru Ota, Anfeng Liu, Ming Zhao, and Tian


