Robust relay node placement in body area networks by heuristic min-max regret

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***Abstract*—A Body Area Network (BAN) is a wireless sensor network where biosensors are placed over or inside the body of a person to collect biomedical data. Designing a BAN essentially consists in deciding the topology of the network and how data are routed from the biosensors to data sinks, while minimizing the total energy consumption. A relevant challenge in the design of BAN is how to take into account the uncertainty of data generation of biosensors in the mathematical optimization models used for designing the network. In this work, we tackle data uncertainty by adopting a min-max regret paradigm and we propose a heuristic approach for solving the corresponding min-max regret optimal design problem. Computational tests on realistic instances indicate that our approach returns design solutions associated with a much lower energy consumption of those returned by an absolute (pure min-max) robustness model, while providing a good level of protection against variations in the data rate.**

***Index Terms*—Body Area Networks; Wireless Sensor Networks; Network Design; Traffic Uncertainty; Robust Optimization; Min-max Regret.**

I. Introduction

In the last decade, there has been increasingly attention towards the use of Wireless Sensor Networks (WSNs) in healthcare applications, where WSNs can support the adoption of more cost efficient and effective patient-oriented technological solutions. For example, WSNs can be adopted to remotely monitor the conditions of patients in a hospital without the intervention of nurses, granting relevant cost savings. An application of WSNs that has recently gained a lot of attention is represented by body area networks. A *Body Area Network* (BAN) is a WSN where wireless sensors (*biosensors*) are placed over or inside the body of a person to collect biomedical data. The biosensors generate data and transmit them to one or more sinks for storing or processing. For a thorough introduction to WSNs and BANs, we address the reader to [12], [22], [23], [25], [28]. The design of a BAN essentially requires to establish the network topology and choose how to route data from the sensors to the collecting sinks. In BAN design a critical objective to pursue is to minimize the total energy consumption associated with power emissions of the BAN wireless devices since: 1) health regulatory bodies impose very strict limits on power emissions for avoiding damages to human tissues due to radio signals and overheating [23]; 2) higher power emissions lead to higher energy consumption and shorter battery lifetime - this a very relevant issue in BANs, where batteries cannot be easily replaced and recharged without badly affecting the patient comfort.

To reduce energy consumption, it is useful to adopt multi-hop routing, implemented through relay nodes, namely wireless devices that act as intermediate nodes between sensors and sinks and allow transmissions over shorter distances consuming less energy (e.g., [19], [20]).

Though BANs have received a lot of attention in literature, especially through works studying the propagation of wireless signals over human bodies and the simulation of routing protocols (see, e.g., [8], [3], [12], [26]), the definition of mathematical optimization models and algorithms for BAN design and management has received limited attention. This lack of optimization tools for BANs has been highlighted also in the relevant works [16], [19]: [19] focused on developing and testing a mixed integer linear program to model relay placement and multi-path data flow routing in BANs; [16] proposed the first robust optimization model for tackling data uncertainty in BANs and a fast heuristic for its solution, based on the Integer Linear Programming heuristic of [13]; the algorithm of [16] has been further improved in [17], granting a sensible increase in design performance.

The main original contribution of the present paper is to propose a new robust optimization model for the problem of designing a BAN taking into account data generation uncertainty of biosensors. As discussed in detail in Section III, tackling data generation uncertainty

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in BAN design is of capital importance: if we do not properly take into account the presence of biosensors with variable data generation rate, as it may happen in healthcare applications, we risk to produce infeasible design solutions that would imply the loss of important biomedical data. Of course, this is a risk that cannot be taken in critical applications connected to the health of people. To deal with data uncertainty we propose to adopt a min-max regret approach [1], which allows to reduce conservatism of solutions with respect to an absolute-robustness approach like that adopted in [16], [17]. However, since solving a min-max regret problem is computationally challenging, we show that a peculiar heuristic application of the min-max regret paradigm can efficiently provide design solutions associated with a contained energy consumption and that grant a very satisfying level of protection against deviations in the input data, when applied to realistic instances.

II. Designing a body area networks

In order to define a mathematical optimization model for the optimal design of BANs, as first step we identify the elements of a BAN that are important for modelling purposes. We can essentially describe a BAN as a set B of wireless sensors deployed over a human body to generate biomedical data that must be collected by a set S of data sinks. To implement a multi-hop routing and improve energy efficiency, the BAN may include relay nodes and we thus introduce a set R to represent the set of relay nodes that can be *potentially* deployed in the BAN: each node $r \in R$ is characterized by a unique position over the body and we must decide whether r is deployed or not. For each biosensor $b \in B$ and for each sink $s \in S$, we denote by $d_{bs} \geq 0$ the volume of data generated by b and intended to be collected by s (d_{bs} is a *bitrate* measured in bit/s). Furthermore, we denote by $c_r \geq 0$ the capacity of a relay node $r \in R$, namely the highest bitrate that r is able to manage.

The transmission of data from any BAN device (biosensor, relay node or sink) to another BAN device is based on a directional wireless link. As in [16], [17], [19], we assume that the BAN uses a Time Division Multiple Access protocol and, consequently, BAN devices can transmit without interference on the same channel.

A natural choice for the optimal design of a BAN is to trace back the design problem to an optimal network flow problem, as done in several works, such as [16], [17], [19]. More precisely, the design problem can be expressed as a capacitated multicommodity flow network design problem, a classical optimization problem where the objective is to establish the topology and capacity of a network and how to route a number of commodities in the network, while minimizing a cost function associated with routing and capacity installation. For an introduction to capacitated network design and multicommodity flows, we refer the reader to [5], [13]. In this work, we refer in particular to the optimization model presented in [16], of which we resume here the main features and elements. We refer the reader to the paper [16] for an exhaustive description of all the modelling considerations that lead to the definition of the optimization model.

In [16], the BAN is modelled through a digraph $G(V, A)$ where: 1) the set of vertices V is the union of the set of vertices representing the biosensors in B, the relay nodes in R and the sinks in S (i.e., $V = B \cup R \cup S$); 2) each arc $a = (i, j)$ in the set of *arcs* A models a directional wireless link from a BAN device (biosensor, relay node or sink) $i \in V$ to another BAN device $j \in V_i$ (here we generically denote by V_i the subset of BAN devices within the communicating range of i). The energy consumed for transmitting one unit of data from a device $i \in V$ to another device $j \in V_i$ is denoted by E_{ij} and is defined as in [10]. Using the previous modelling assumptions, we provide the following definition of BAN design problem, introduced in [16]:

Definition 1: The Body Area Network Design Problem (BAND) - Given: 1) a BAN modeled as a directed graph $G(V, A)$; 2) the bitrate $d_{bs} \geq 0$ of data generated by each biosensor $b \in B$ for each sink $s \in S$; 3) the capacity $c_r \geq 0$ of each relay $r \in R$; 4) the energy coefficients $E_{ij} \geq 0$ expressing the total energy consumed to send 1 data unit from i to j; the BAND consists in choosing which relays are deployed and which paths are used to route the biosensor-sink flow of data, in order to minimize the total energy consumption.

According to the definition of BAND, we must thus take two major decisions: 1) which relays are deployed and 2) which paths are employed to route the data generated by each biosensor for each sink. We can model these decisions by defining two families of binary decision variables: 1) binary *relay deployment variables* $y_r \in \{0, 1\} \ \forall\, r \in R$ such that y_r equals 1 if relay r is deployed and 0 otherwise; 2) binary *unsplittable flow variables* $x_{ij}^{bs} \in \{0, 1\} \ \forall\, b \in B, s \in S, (i, j) \in A$ such that x_{ij}^{bs} equals 1 if all the data generated by biosensor b for sink s are routed on arc (i, j) and 0 otherwise. These variables are used in the following ILP problem introduced in [16] and denoted by BAND-ILP:

$$\min \sum_{b \in B} \sum_{s \in S} \sum_{(i,j) \in A} E_{ij} d_{bs} x_{ij}^{bs} \qquad \text{(BAND-ILP)}$$

$$- \sum_{\substack{(b,j) \in \\ A_{B \to R} \cup A_{B \to S}}} x_{bj}^{bs} = -1 \qquad b \in B, s \in S \tag{1}$$

$$\sum_{\substack{(j,r) \in \\ A_{B \to R} \cup \\ \cup A_{R \leftrightarrow R}}} x_{jr}^{bs} - \sum_{\substack{(r,j) \in \\ A_{R \leftrightarrow R} \cup \\ \cup A_{R \to S}}} x_{rj}^{bs} = 0 \qquad b \in B, s \in S, r \in R \tag{2}$$

$$\sum_{\substack{(j,s)\in \\ A_{B\to S}\cup \\ \cup A_{R\to S}}} x_{js}^{bs} \;=\; 1 \qquad\qquad b \in B, s \in S \tag{3}$$

$$\sum_{\substack{(r,j)\in \\ A_{R\leftrightarrow R}\cup \\ \cup A_{R\to S}}} d_{bs}\, x_{rj}^{bs} \;\leq\; c_r\, y_r \qquad r \in R \tag{4}$$

$$\sum_{r\in R} y_r \leq U \tag{5}$$

$$x_{ij}^{bs} \in \{0,1\} \qquad\qquad b \in B, s \in S, (i,j) \in A$$

$$y_r \in \{0,1\} \qquad\qquad r \in R\,.$$

The objective function expresses the minimization of the total BAN energy consumption, considering the summation of energy consumed for transmissions over all the arcs of the graph (specifically, the consumption over one arc (i,j) is the sum of the consumption of all biosensor-sink couples that route their data on (i,j), expressed as the product of the unitary energy consumption E_{ij} by the amount of data d_{bs} of a biosensor-sink couple (b,s)).

The constraints (1)-(3) are flow conservation constraints expressing the balance between ingoing and outgoing flows depending upon the nature of the considered BAN node (see [16] for a detailed description of each family of flow conservation constraints - here we just recall that: the set $A_{B\to S}$ contains arcs such the tail is a biosensor and the head is a sink; the set $A_{B\to R}$ is those of arcs such that the tail is a biosensor and the head is a relay node; the set $A_{R\leftrightarrow R}$ is those of arcs such that both the tail and the head are relay nodes; the set $A_{R\to S}$ is those of arcs such that the tail is a relay node and the head is a sink). The constraints (4) model the capacity of each relay node through a right-hand-side with variable value: if node r is not deployed (i.e., $y_r = 0$), the right-hand-side is zero and no data can pass through node r. If instead the node is deployed (i.e., $y_r = 1$), the right-hand-side "is activated" and is equal to c_r. The single constraint (5) expresses that we can deploy at most a number $U > 0$ of relay nodes in the network.

III. Robust BAN design

The BAN design problem that we have considered until now is based on the assumption that all the input data of the problem are exactly known when the problem is solved. However, this may be not true in practice, where it is likely to have sensors that generate data according to a rate not known a priori: as an example, one can think about event-driven biosensors that generate data only when a special body event occurs (see e.g., [12]). As it is well-known in mathematical optimization, data uncertainty in an optimization problem must be carefully addressed and its disregard may have very bad effects: if deviations in the input data occur, optimal solutions may reveal to be of very bad quality of even infeasible (see [6], [7], [11] for a thorough discussion). As a consequence, it is necessary to address data uncertainty through some mathematical optimization paradigm that guarantees solutions to remain feasible and optimal even in presence of deviation in the input data.

In the case of BAN design, the question of how addressing data uncertainty has been first addressed in the papers [16], [17], which adopt an absolute robustness paradigm, according to which the design solution must maintain its feasibility under all possible considered deviations. More formally, assume that the data rate d_{bs} of a biosensor-sink couple is uncertain and that it can assume any value in a finite set $D_{bs} = \{d_{bs}^1, d_{bs}^2, \ldots, d_{bs}^k\}$ (w.l.o.g., we assume that the value are sorted increasingly). Let us denote by: $\mathcal{D} = D_{11} \times \cdots \times D_{bs} \times \cdots \times D_{|B||S|}$ the set of all the $|B||S|$-tuples that can be obtained by considering all the possible combinations of data generation values for all the biosensor-sink couples.

According to the absolute robustness paradigm, we aim to find an optimal solution that grants the best performance under the worst uncertain data realization case. More formally, if we denote by $\mathcal{F}$ the set of all feasible solutions (x,y) of the problem BAND-ILP and by $E[(x,y),d]$ the objective function of the problem, highlighting the dependency upon the decision vector (x,y) and a data generation scenario $d \in \mathcal{D}$, the absolute robustness problem for BAND can be compactly written as: $\min_{(x,y)\in\mathcal{F}} \ \max_{d\in\mathcal{D}} \ E[(x,y),d]$. This corresponds to find a feasible solution (x^*,y^*) that grants the minimum energy consumption under the worst data generation scenario contained in $\mathcal{D}$ (see [1]). An optimal solution to this problem is in particular protected against *all* the possible realization of data identified in $\mathcal{D}$. This comes however at the so-called "price of robustness" (e.g., [6], [11]): granting protection against data uncertainty leads to a deterioration in the value of the optimal solution, caused in general by excluding solutions that do not remain feasible under all the possible scenarios.

The absolute robustness paradigm is very appropriate in BAN design problems where not considering possible data generation scenarios could lead to the death of the patient, such as BANs aimed at early detecting ischemia. In contrast, as discussed for example in [1], [4], [7], this paradigm may result too conservative in less critical (BAN) applications where we want to grant a consistent level of protection against data uncertainty while excluding extreme scenarios whose occurrence is possible but unlikely. In this paper, focusing on this latter typology of BAN deployments, we decided to rely on the *min-max regret paradigm*, an alternative less conservative robustness paradigm. For an exhaustive introduction to min-max regret, we refer the reader to [1], [21]. Min-max regret is based on using a so-called *regret* measure: for a given solution (x,y) and a data scenario

d, the regret $R[(x,y),d]$ quantifies the loss in value that we must face when implementing a solution (x,y) instead of the optimal solution $(x^*,y^*)_d$ for scenario d, formally: $R[(x,y),d] = E[(x,y),d] - E[(x^*,y^*)_d,d]$. The maximum regret $R^{\max}(x,y)$ for a solution (x,y) is equal to the maximum regret measure considering all the data scenarios, i.e. $R^{\max}(x,y) = \max_{d\in\mathcal{D}} R[(x,y),d]$. In the min-max regret paradigm the aim is to find a feasible solution that minimizes the maximum regret considering all data rate generation scenarios, i.e.:

$$\min_{(x,y)\in\mathcal{F}} \max_{d\in\mathcal{D}} R[(x,y),d] \ . \qquad (6)$$

As discussed in [20], one of the drawback of the min-max regret approach under the setting that we considered is that, in order to find the maximum regret of a particular solution (x,y), we potentially need to evaluate an exponential number of scenario, in particular finding their optimal design solution. To tackle this, [20] proposes to adopt a heuristic min-max regret for a general wireless sensor network design problem that refers to what we call a *pessimistic median* data realization scenario. We propose here a version of this heuristic approach adapted to deal with data generation uncertainty in BAN design.

Following [20], we first define the median data rate generation scenario d^{med} as that including for each biosensor-sink couple (b,s) the data rate value $\bar{d}_{bs} \in D_{bs}$ that is closest to the median value of the data rates in D_{bs}. Then we compute an optimal design solution $(x,y)^{med}$ to the problem BAND-ILP using d^{med} as data rate values. This solution should provide on average a good design, but could become infeasible due to realizations of data rates that are higher than the medians. As a consequence, we characterize a worse data rate scenario by identifying the set of so-called *favored* biosensor-sink couples $\bar{C} \subseteq C$: these are couples that in the optimal solution $(x,y)^{med}$ benefit from the presence of relay nodes, having their data flow passing through the relay nodes and thus reducing energy consumption. A pessimistic median scenario can be obtained by assuming that the favured couples $(b,s) \in \bar{C}$ experience a reduction in their data rates and have a data rate equal to their lowest value d^1_{bs} in D_{bs}, while the non-favored couples $(b,s) \notin \bar{C}$ experience a data rate increase and have a data rate equal to the highest value d^k_{bs} in D_{bs}. So we define the Pessimistic Median (PM) data rate scenario as:

$$d^{PM}_{bs} = \begin{cases} d^1_{bs} & if(b,s) \in \bar{C} \\ d^k_{bs} & if(b,s) \notin \bar{C} \end{cases}$$

The heuristic min-max regret approach consists in approximating the complete problem (6) considering only the scenario d^{PM}, i.e. we solve the problem:

$$\min_{(x,y)\in\mathcal{F}} R[(x,y),d^{PM}] \quad .$$

Solving this problem actually reduces to solve the (deterministic) BAND-ILP with data rates equal to d^{PM}.

IV. Preliminary computational results

We evaluated the performance of the heuristic min-max regret approach on 20 instances considering a BAN including 2 sinks, 16 biosensors and 400 potential relay nodes locations over the human body We assume that the biosensors and sinks possess the capacity that is needed to process all the data that they respectively transmit and receive, whereas we assume that the relays have a capacity of $c_r = 250$ kbit/s. Each biosensor may assume 20 possible data rate generation values randomly chosen in the range [50,200] bit/s. Due to lack of space, we refer the reader to [16] for a detailed discussion about how the energy coefficients E_{ij} are derived in the instances.

The computational tests were made on a 1.80 GHz Intel Core 2 Duo processor with 2 GB of RAM, using a C/C++ code interfaced by Concert Technology with the optimization software IBM ILOG CPLEX 12.1 and with CPLEX running with default settings. Our aim is to evaluate the trade-off between reduction of protection and solution conservatism of the heuristic min-max regret approach with respect to the the absolute robustness approach and the use of the median data rate scenario. Specifically, we evaluated the increase in energy consumption associated with the optimal solution of the pessimistic median scenario d^{PM} (i.e., the solution of the heuristic min-max regret approach) and with the optimal solution for the absolute-robustness scenario (i.e., the case where all the biosensors generate data according to their highest rate allowed in $\mathcal{D}$ - we denote such scenario by d^{ROB}) with respect to the optimal solution for the median data rate scenario d^{med}. Furthermore, given 1000 data rate scenarios randomly extracted from $\mathcal{D}$, we assess for how many scenarios the optimal solution for d^{med} and for d^{PM} remains feasible (i.e., the solution does not violate any constraint of BAND-ILP with data rate coefficients equal to those of the considered scenario).

The results of the computational tests are presented in Table I. In the table: ID identifies the instance; ΔE% (d^{PM} VS d^{med}) and (d^{ROB} vs d^{med}) is the percentage increase in energy consumption entailed by d^{PM} and d^{ROB} with respect to d^{med}, respectively; $PROT\%$ is the percentage of randomly generated data rate scenarios for which an optimal solution of d^{med} and d^{PM} is feasible.

Looking at the table, the first evident fact is that the adoption of absolute-robustness leads to identifying very conservative optimal solutions that, though granting full protection against all possible data rate scenarios, leads to a huge increase in energy consumption with respect to the median and pessimistic median case. On average, the increase in energy ΔE% (d^{ROB} vs d^{med}) is more than three times, reaching 219%, and can even reach a level close to 4 times the energy consumption of the median case (instance I15). We believe that this is a too high

Table I
COMPUTATIONAL RESULTS

ID	ΔE%		PROT%	
	(d^{PM} VS d^{med})	(d^{ROB} vs d^{med})	d^{med}	d^{PM}
I1	118.93	175.34	53.2	79.8
I2	76.00	215.96	57.6	76.5
I3	93.91	168.03	46.9	73.7
I4	125.16	159.77	53.8	81.0
I5	139.46	284.11	52.4	82.8
I6	114.42	242.89	54.7	77.3
I7	89.77	220.68	49.8	81.1
I8	96.61	264.56	54.4	76.2
I9	82.90	191.00	57.4	76.9
I10	119.76	211.71	61.3	84.7
I11	109.31	228.64	59.5	78.6
I12	91.47	209.22	57.5	82.6
I13	133.14	243.89	58.9	78.0
I14	89.33	199.01	62.0	73.1
I15	93.06	276.40	42.0	83.4
I16	94.34	176.06	58.2	77.0
I17	114.00	238.30	44.8	79.5
I18	80.04	247.45	49.0	85.6
I19	73.25	227.00	57.4	81.8
I20	79.83	206.18	59.3	83.4

price to pay for non-critical BAN applications where we may accept the risk of infeasibilities due to deviations in the data rates. In contrast, using the heuristic min-max regret based on d^{PS} we get a high satisfying level of protection that is on average equal to about 79% and can be over 80% in many cases, while at the same time entailing a much more contained energy consumption, which, on average, is about two times higher with respect to d^{med}. This is an attractive performance that deserves to be further investigated, in particular by exploring refined definitions of the reference scenario adopted in the heuristic min-max regret approach.

As future work, we intend to study the integration of signal-to-interference quantities in the model, developing branch-and-cut solution methods identifying conflicts between variables, as in [9], [14], [15]. Also, we plan to study biobjective versions of the design problem, evaluating the trade-off between relay cost and energy consumption and adopting a solution algorithm as in [27]. Last but not least, we plan to include routing models enabling a fair energy consumption over the links, following approaches like [2], [18], [24].

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