A Multicommodity Formulation for Routing in Healthcare Wireless Body Area Networks

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Keywords: Healthcare wireless body area networks, Multicommodity netflow formulation, Variable neighborhood search metaheuristic.

Abstract: In this paper, we propose a minmax multicommodity netflow model for routing in healthcare wireless body area networks (WBAN). The model is aimed at minimizing the worst power consumption of each bio-sensor node placed in the body of a patient plus the total heating costs subject to flow conservation and maximum capacity energy constraints. The model is formulated as a mixed integer linear program (MILP). Thus, we propose a variable neighborhood search (VNS) metaheuristic procedure to come up with tight near optimal solutions. Our preliminary numerical results indicate the VNS approach obtains near optimal solutions with integrality gaps no larger than 3.5 %. Finally, since the proposed model has two conflicting objectives, i.e, heating costs and worst power consumption, we adopt a weighted sum criteria for each objective in order to analyze the behavior of the model.

1 INTRODUCTION

Wireless sensor networks (WSN) have become one of the most promising technologies to enhance quality of life around the globe. So far, there are applications for entertainment, testing weather conditions, traveling location, retail industries, military logistics, healthcare systems, and so on. Regarding healthcare systems, a major concern is to address the problem of pervasive preventive monitoring systems. Specially for elderly population whose growth is directly proportional to the development of countries (Kinsella and Phillips, 2005). Moreover, this technology would allow not only the elderly and chronically ill people to be monitored, but also to provide high quality care services for little children in situations where both parents have to work. It would also help people living in rural areas where reaching hospitals and medical centers is more difficult. A major research challenge in healthcare monitoring systems so far is the development of new applications by integrating efficient wireless body area networks (WBAN) with electronic devices such as mobile phones, laptop computers, desk computers or tablets (Schmidt and Laerhoven, 2001). For example, being at home, a wireless personal area network (WPAN) may provide residents and caregivers with continuous medical monitoring, control of home appliances, and emergency communication (Stanford, 2002; McFadden and Indulska, 2004). A WBAN is composed of tiny biological sensors (bio-sensors) which are placed in the body of a person in order to remotely monitor healthcare status conditions such as fever, blood pressure, body temperature, heart rate, blood glucose concentration, among many others. Unlike typical WSN, WBAN suffer from very limited energy resources and hence preserving the energy of the nodes is of great importance. Additionally, an extremely low transmit power per node is required in order to minimize interference and to cope with health concerns such as avoiding tissue heating of skin on patients. One possible approach to minimize power consumption as well as tissue heating of skin problems is by improving the performance of routing protocols. So far, there have been proposed some algorithmic approaches to control bio-effects for WBAN. The authors in (Tang et al., 2005) propose a Thermal Aware Routing Algorithm (TARA) that balances the communication over the sensor nodes in order to route data away from high temperatures. The algorithm achieves better energy efficiency levels and low temperatures, however it requires that all nodes have complete knowledge about the temperatures of all remaining nodes in the network. Another attempt is a protocol known as Anybody (Watteyne et al., 2007). The underlying idea of Anybody is to form clusters and a backbone network with selected cluster heads in order to reduce the number of direct transmissions to the sink node. This algorithm also achieves energy savings, but it does not consider other aspects such as reliability of messages for example. In (Fang and Dutkiewicz, 2009), the authors propose an energy efficient medium access control (MAC) protocol referred to as BodyMAC which uses flexible bandwidth allocation to improve node energy efficiency. Besides, it includes a new efficient sleep mode so as to reduce the idle listening duration. In (Kwak et al., 2009), the authors compare and analyze different protocols from WBAN requirements to energy efficiency whereas in (Huang et al., 2010) the authors propose a weighted random value protocol for multiuser WBANs (WRAP). Other efforts consider explicit mathematical programming formulations in order to efficiently design optimal routing protocols in WBANs (Abouzar et al., 2011; Ababneh et al., 2012a; Ababneh et al., 2012b; Elias and Mehaoua, 2012; Yan et al., 2012; Awad et al., 2013). In a WBAN routing protocols must have self-configuration features and must be capable of finding the best route for communication in order to increase delivery insurance and decrease energy consumption between nodes that comprise the network.

WBAN is an emerging research field where new routing protocols are mandatorily needed to minimize power consumption at each node while simultaneously maximizing the lifetime of each node in the network. In this paper, we present a minmax multicommodity netflow formulation to optimally route sensed information by nodes in a WBAN. The model minimizes the worst power consumption of each bio-sensor plus the total heating costs produced by the nodes subject to flow conservation and maximum power available constraints for each node. The model is formulated as a mixed integer linear program (MILP) and thus, we propose a variable neighborhood search (VNS) metaheuristic procedure to compute tight near optimal solutions.

The paper is organized as follows. Section 2 presents the multicommodity netflow formulation under study. In section 3, we present the VNS procedure to compute near optimal solutions. In section 4, we provide preliminary numerical results for the VNS approach when compared to the optimal solution of the problem. Since the proposed model has two conflicting objectives, i.e, heating costs and worst power consumption, here we also consider a weighted sum criteria for each objective and numerically compare the model behavior. Finally, in section 5, we conclude the paper.

2 PROBLEM FORMULATION

We model a fixed WBAN by the means of a graph $G = (N,A)$, where N denotes the set of sensor (bio-sensor) nodes and A is a set of directed arcs. The assumption of directed arcs is valid for WBANs since before any message is transmitted, the route between the source and the destination can be established using Ad-hoc On-demand Distance-Vector routing (AODV) protocols (Perkins and Royer, 1999). Without loss of generality, we assume that every node has a fixed initial power capacity $E \in \mathbb{R}^+$. The set of nodes N is composed of a subset of source nodes N_s which sense and collect the data to be transmitted, a set of intermediate transmitters N_I and a set of sink nodes N_t where all data is received. For each node $j \in N$ we define the sets $\delta^-(j) = \{i \in N : (i,j) \in A\}$ and $\delta^+(j) = \{i \in N : (j,i) \in A\}$. We denote by C the set of commodities to be transmitted where each commodity $c \in C$ consists of routing D_c packets from a source node $i \in N_s$ to a destination node $j \in N_t$. Let $e_{i,j}$ denote the unitary energy needed for transmission of packets on arc $(i,j) \in A$ and define the total energy consumption of node $j \in N$ as $\sum_{c \in C} \sum_{i \in \delta^-(j)} e_{i,j} D_c f^c_{i,j}$ where $D_c f^c_{i,j}$ is the number of packets of commodity c transmitted on arc (i,j). Note that this amount of energy is computed under the assumption that the transmission energy requirement is negligible compared to the energy required for receiving packets at each node. This is valid assumption since an extremely low transmit power per node is required in short range ultra-wide band in WBANs and thus the effort is considerably higher when the nodes are receiving packets (Shi et al., 2011). Moreover, this allows significant energy savings when using network coding techniques with the objective of providing reliability under low-energy constraints (Arrobo and Gitlin, 2011; Shi et al., 2011). We consider the following multicommodity netflow formulation denoted hereafter by P_0 as

$$\min_{f,x} \quad \left\{ \sum_{i \in N} a_i x_i + \max_{j \in N} \sum_{c \in C} \sum_{i \in \delta^-(j)} e_{i,j} D_c f^c_{i,j} \right\} \quad (1)$$

$$\text{s.t.} \quad \sum_{j \in \delta^+(i)} f^c_{i,j} - \sum_{j \in \delta^-(i)} f^c_{j,i} = b^c_i, \quad \forall i \in N; c \in C \quad (2)$$

$$\sum_{c \in C} \sum_{i \in \delta^-(j)} e_{i,j} D_c f^c_{i,j} \leq E x_j, \forall j \in N \quad (3)$$

$$-x_i \leq b^c_i \leq x_i, \quad \forall i \in N; c \in C \quad (4)$$

$$f^c_{i,j} \in [0,1], \forall (i,j) \in A; c \in C \quad (5)$$

$$x_i \in \{0,1\}, \forall i \in N \quad (6)$$

where the flow variables $f^c_{i,j}$ represent the portion of commodity $c \in C$ to be transmitted on an arc $(i,j) \in A$.

The binary variables $\{x_i, i \in N\}$ are used to decide whether node $i \in N$ will be active or not when transmitting packets through the network. The objective function in (1) is to minimize the total heating costs $\{a_i, i \in N\}$ produced by bio-sensors which are placed in the body of a patient plus the worst case power consumption of each active node in the network. The latter is a crucial aspect in a WSN since by definition, its lifetime is equal to the minimum lifetime of all nodes in the network (Deb, 2002; Jourdan and de Weck, 2004). In other words, the network lifetime ends as soon as any node runs out of its battery. Let b_i^c be equal to 1 if node $i \in N_s$, or be equal to -1 if node $i \in N_t$, and zero otherwise. Constraint (2) are flow conservation constraints for each node $i \in N$ and for each commodity $c \in C$ while constraint (3) imposes the condition that each node has a maximum available power to receive packets in the network. Note that this constraint is forced to be equal to zero when its respective node is set to an inactive state condition. Constraint (4) imposes the condition that all source and sink nodes should always be active, otherwise the network can not sense or relay the data collected at the sink node. Finally, constraints (5)-(6) are the domain constraints. Note that model P_0 can be easily converted into a mixed integer linear programming (MILP) problem by introducing an upper bounding variable z instead of using the max term in its objective function as follows.

$$
\begin{aligned}
P_1 \quad & \min_{f,x} \quad z + \sum_{i \in N} a_i x_i \\
\text{s.t.} \quad & z \geq \sum_{c \in C} \sum_{i \in \delta^-(j)} e_{i,j} D_c f_{i,j}^c, \quad \forall j \in N \\
& \sum_{j \in \delta^+(i)} f_{i,j}^c - \sum_{j \in \delta^-(i)} f_{j,i}^c = b_i^c, \quad \forall i \in N; c \in C \\
& \sum_{c \in C} \sum_{i \in \delta^-(j)} e_{i,j} D_c f_{i,j}^c \leq E x_j, \quad \forall j \in N \\
& -x_i \leq b_i^c \leq x_i, \quad \forall i \in N; c \in C \\
& f_{i,j}^c \in [0,1], \forall (i,j) \in A; c \in C \\
& x_i \in \{0,1\}, \forall i \in N
\end{aligned}
$$

We remark that model P_1 could be considered as part of any existing WBAN MAC protocol (See references in section 1) as it provides an optimal routing strategy. However, it does not consider other technical aspects such as broadcasting control flows and organization of the network. The routing strategy is mandatory in WBANs as it allows significant power savings when transmitting sensed data through the network (Ababneh et al., 2012b; Elias and Mehaoua, 2012; Yan et al., 2012; Awad et al., 2013). For a more general, comprehensive and technological perspective regarding WBANs protocols, we refer the reader to the works in (Ullah et al., 2010; Ullah et al., 2012).

In the next section, we propose a variable neighborhood search metaheuristic approach to compute near optimal solutions for P_1.

3 THE VNS APPROACH

Metaheuristics are simple algorithmic procedures commonly used to find near optimal (suboptimal) solutions for combinatorial optimization problems. In practice, they have proven to be highly effective when solving many of these hard problems (Glover and Kochenberger, 2003). Especially when the dimensions of the problem increase rapidly which is often the case in real world applications and where no solver is available to solve these problems to optimality. Perhaps, the most frequently utilized metaheuristics approaches are genetic algorithms, tabu search, ant colony system, particle swarm optimization, variable neighborhood search, simulated annealing, among others. For a more detailed explanation on how these metaheuristics approaches work, we refer the reader to the book in (Glover and Kochenberger, 2003). In principle, a genetic algorithm or a tabu search approach would also serve to compute feasible solutions for our proposed multicommodity flow formulation in a straightforwardly manner. In this paper, we choose VNS mainly due to its simplicity and low memory requirements. In particular, we adopt a reduced VNS strategy which drops the local search phase of the basic VNS algorithm as it is the most time consuming step (Hansen and Mladenovic, 2001; Hansen et al., 2001). In order to compute feasible solutions for problem P_1 using a VNS approach, we observe that for any fixed assignment of vector $x = \bar{x}$ in P_1, the problem reduces to solve the following linear programming problem

$$
\begin{aligned}
\bar{P}_1 \quad & \min_{f} \quad z \\
\text{s.t.} \quad & z \geq \sum_{c \in C} \sum_{i \in \delta^-(j)} e_{i,j} D_c f_{i,j}^c, \quad \forall j \in N \\
& \sum_{j \in \delta^+(i)} f_{i,j}^c - \sum_{j \in \delta^-(i)} f_{j,i}^c = b_i^c, \quad \forall i \in N; c \in C \\
& \sum_{c \in C} \sum_{i \in \delta^-(j)} e_{i,j} D_c f_{i,j}^c \leq E \bar{x}_j, \quad \forall j \in N \\
& f_{i,j}^c \in [0,1], \forall (i,j) \in A; c \in C
\end{aligned}
$$

There are $2^{|N|-|N_s|-|N_t|}$ feasible assignments for vector x. It is obvious that some of them are not feasible as they might turn problem $\bar{P}_1$ infeasible. We propose a VNS approach to compute feasible solutions for P_1 by randomly generating these binary vectors.

VNS is a recently proposed metaheuristic approach (Hansen and Mladenovic, 2001) that uses the

Figure 1: VNS Algorithm

Input: A problem instance of P_1
Output: A feasible solution $(\tilde{x}, \tilde{f}, \tilde{v})$ for P_1

Step 0:
$Time \leftarrow 0$; $\mathcal{H} \leftarrow 1$;
$count \leftarrow 0$; $x_i \leftarrow 0, \forall i \in N \setminus N_s \cup N_t$
$x_i \leftarrow 1, \forall i \in N_s \cup N_t$
Step 1:
For $st = 2$ to St
  $r \leftarrow min(a_i, i \in N_{st})$
  $x_r \leftarrow 1$
end
Solve the linear problem $\bar{P}_1$.
Let $(\bar{x}, \bar{f}, \bar{v})$ be the optimal solution of $\bar{P}_1$ with objective function value $\bar{v}$
$\bar{v} \leftarrow \bar{v} + \sum_{i \in N} a_i \bar{x}_i$
$(\tilde{x}, \tilde{f}, \tilde{v}) \leftarrow (\bar{x}, \bar{f}, \bar{v})$
Step 2:
while $(Time \leq maxTime)$
  For $j = 1$ to $\mathcal{H}$
    choose randomly $i' \in N_I$
    if $(x_{i'} = 0)$ $x_{i'} \leftarrow 1$
    else $x_{i'} \leftarrow 0$
    end if
  end for
  Solve the linear problem $\bar{P}_1$.
  Let $(\bar{x}, \bar{f}, \bar{v})$ be the optimal solution of $\bar{P}_1$ with objective function value $\bar{v}$
  $\bar{v} \leftarrow \bar{v} + \sum_{i \in N} a_i \bar{x}_i$
  Let $(\bar{x}, \bar{f}, \bar{v})$ be the new solution found for P_1 with objective value function $\bar{v}$
  if $(\bar{v} < \tilde{v})$
    $\mathcal{H} \leftarrow 1$; $(\tilde{x}, \tilde{f}, \tilde{v}) \leftarrow (\bar{x}, \bar{f}, \bar{v})$
    $Time \leftarrow 0$; $count \leftarrow 0$
  else
    Keep previous solution
    $count \leftarrow count + 1$
    if $(\mathcal{H} \leq |N_I|)$ and $(count > \eta)$
      $\mathcal{H} \leftarrow \mathcal{H} + 1$; $count \leftarrow 0$
    end if
  end if
end while

idea of neighborhood change during the descent toward local optima and to avoid the valleys that contain them. We define the neighborhood structure $Ng(x)$ for P_1 as the set of neighbor solutions x' in P_1 at a distance "h" from x where the distance "h" corresponds to the Hamming distance between the binary vectors x and x', respectively. In our numerical tests, without loss of generality, we adopt a grid layout configuration as depicted in Figure 2 where a directed graph shows that bio-sensor nodes are placed in each stage. In particular, in stage 1 we have the source nodes, from stage 2 to the final stage we have the intermediate nodes. Finally, we have only one node acting as a sink node to receive all sensed and collected information sent by the source nodes through the network. We denote by N_{st} the number of nodes placed at stage $st \in \{1, .., St\}$ where St refers to the final stage in Figure 2. We fur-

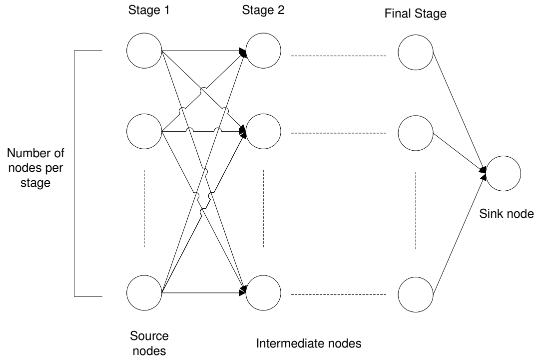

Figure 2: WBAN with grid layout configuration.

ther assume that all nodes at each stage are consecutively connected with those of the next stage (Arrobo and Gitlin, 2011). We also assume that the number of nodes at each stage is the same, i.e., $N_1 = \cdots = N_{St}$. The grid layout configuration is a valid assumption in WBANs as it provides more reliable communications when using cooperative network and diversity coding transmission schemes with enhanced throughput (Arrobo and Gitlin, 2011). There are other network configurations such as star, tree, mesh (Ullah et al., 2012) and grid topologies in the literature (Arrobo and Gitlin, 2011). The most common topology is a star one where the nodes are connected to a central coordinator in star manner (Ullah et al., 2012). However, the star configuration follows a single hop strategy which is not always the best choice. In (Reusens et al., 2009), the authors discuss about energy efficient topology designs for WBANs. They consider a tree network topology and discuss on the energy savings when using single hop and multi hop strategies. They conclude that the distance between nodes plays an important role and that both single hop or multi hop strategies achieve energy savings under different conditions (Reusens et al., 2009).

The VNS approach we propose is presented in Figure 1. It receives an instance of problem P_1 as input and provides a tight feasible solution for it. We denote by $(\tilde{x}, \tilde{f}, \tilde{v})$ the final solution obtained with the algorithm where $\tilde{v}$ represents the objective function value. The algorithm is simple and works as follows. In Step 0, we initialize all the required variables. Then, in Step 1 we obtain an initial feasible assignment for vector $x = \bar{x}$ by simply setting $\bar{x}_r = 1$ such that $r = min(a_i, i \in N_{st})$ is the minimum value for that particular stage. This allows solving $\bar{P}_1$ and obtaining an initial feasible or infeasible solution $(\tilde{x}, \tilde{f}, \tilde{v})$ for P_1 that we keep. During the execution of the while loop in the VNS algorithm, if for any $x = \bar{x}$ model $\bar{P}_1$ is infeasible, then the solution is discarded and not considered as a valid solution. Next, the algorithm performs a variable neighborhood search by randomly assigning binary values in $\mathcal{H} \leq |N_I|$ positions of vector x where these positions belong to the set N_I. Initially, $\mathcal{H} \leftarrow 1$ while it is increased in one unit when there is no improvement after new "η" solutions have been evaluated. On the other hand, if a new current solution is better than the best found so far, then $\mathcal{H} \leftarrow 1$, the new solution is recorded and the process goes on. The whole process is repeated until the cpu time variable "*Time*" is less than or equal to the maximum available "*maxTime*". Note we reset "*Time* $\leftarrow$ 0" when a new better solution is found. This gives the possibility to search other "*maxTime*" units of time with the hope of finding better solutions.

4 NUMERICAL RESULTS

In this section, we first present preliminary numerical results for the proposed VNS approach using only one sample for the input data of the instances. Subsequently, we provide preliminary numerical comparisons for P_1 while adopting a weighted sum criteria for the objective function of P_1 in order to analyze the behavior of the model. Finally, we compute average numerical results.

4.1 Numerical results for the VNS approach

In order to present preliminary numerical results for problem P_1 using the proposed VNS algorithm, the input data is randomly generated as follows. The entries in matrix $(e_{i,j})$ are uniformly drawn from $[0,1]$ while the heating costs $\{a_i, i \in N\}$ and packets $\{D_c, c \in C\}$ are uniformly distributed in $[0,10]$. The maximum available energy for each node is set equal to $E = 0.4 * \sum_{i \in N} e_{i,1} * \frac{\sum_{c \in C} Dc}{|C|}$. The value of η in the VNS algorithm is calibrated to $\eta = 20$. We set the maximum number of commodities be equal to $|C| = |N_s|$, i.e. we assume that each source node can only sense one type of commodity. This is a valid assumption as bio-sensors are usually designed for sensing specialized information in a WBAN. Finally, we set the parameter $maxTime = 100$. A Matlab program is implemented using CPLEX 12 to solve problem P_1, its linear programming (LP) relaxation, and each LP relaxation $\bar{P}_1$ within each iteration of the VNS algorithm. The numerical experiments have been carried out on a Pentium IV, 1 GHz with 2 GoBytes of RAM under windows XP. In Table 1, column 1 shows the number of nodes considered in each instance. Commonly, the maximum number of nodes in WBANs can be up to 256 nodes (Fang and Dutkiewicz, 2009). Columns 2 and 3 show the number of stages and number of nodes per stage for each of the instances. Columns 4 and 5 provide the optimal solution of P_1 and the cpu time in seconds CPLEX needs to get that solution. Columns 6 and 7 provide the optimal solutions for the LP relaxation of P_1 and the CPLEX cpu time in seconds as well. Similarly, columns 8 and 9 show the best solution found with the VNS approach and its cpu time in seconds. Finally, columns 10, 11 and 12 give the gaps for the LP relaxation, the gaps obtained using the initial solution of the VNS approach and the gaps for the best solution found with the VNS approach, respectively. The gaps are computed as $\text{Gap}_{LP}=\left(\frac{P_1 - LP_1}{P_1}\right) * 100$ for the LP case, $\text{Gap}_{VNS}^{Ini}=\left(\frac{VNS_{ini} - P_1}{P_1}\right) * 100$ for the initial solution obtained with the VNS algorithm and $\text{Gap}_{VNS}=\left(\frac{VNS - P_1}{P_1}\right) * 100$ for the best solution found with VNS, respectively. The numerical results presented in Table 1 are computed using only one sample for the input data of each instance. From Table 1, we mainly observe that the gaps obtained with the VNS algorithm are near optimal for all the instances we test, e.g. not larger than 3 % from the optimal solution of the problem. Regarding the cpu times, we observe that the VNS approach requires more time when the number of stages is less than the number of nodes per stage. Furthermore, this cpu time is even larger than the time required by CPLEX. This is easy to check for instances with 61 nodes in Table 1, for example. From our preliminary numerical results, we observe that this is mainly caused by the fact that the VNS approach needs to solve many linear programs in this case. Ultimately, we observe that the gaps obtained when using the initial solutions found with VNS are not very tight which shows somehow the effectiveness of the VNS approach. On the other hand, when the number of stages is larger than the number of nodes per stage, we observe that the VNS approach is significantly faster than CPLEX. Moreover, in this case we see that the initial solution found with the proposed algorithm is very tight and in some cases optimal, e.g. this is the case for instances with 49 and 61 nodes. In particular, we see that the cpu time required by CPLEX becomes prohibitive for some of these instances. Finally, we observe that the gaps obtained with the LP relaxation of P_1 are far from the optimal solution of the problem.

Table 1: Numerical results for the VNS approach

N	# stages	nodes/stage	P_1	cpu(s)	LP_1	cpu(s)	VNS	cpu(s)	Gap$_{LP}$ %	Gap$^{Ini}_{VNS}$%	Gap$_{VNS}$%
13	3	4	31.5214	1.8120	24.6043	0.7340	31.5214	0.3910	21.9442	13.9145	0
46	3	15	89.0458	2.5000	81.0329	1.9060	89.0458	67.4370	8.9986	26.4712	0
61	3	20	141.9789	5.7810	125.7967	4.3280	142.3221	1044.1710	11.3976	17.6738	0.2418
17	4	4	53.2150	0.8910	32.0876	0.7500	53.2150	0.0320	39.7019	2.1233	0
61	4	15	99.6237	10.9060	91.0988	3.2190	99.6858	222.8290	8.5571	22.8606	0.0623
21	5	4	51.7760	0.7660	46.6627	0.7340	51.7760	0.0010	9.8757	0	0
41	5	8	73.5483	16.3120	50.3013	1.2030	73.5483	135.1730	31.6078	17.6137	0
51	5	10	63.5951	12.7030	50.8429	1.7970	65.2285	208.0150	20.0522	38.6343	2.5685
33	8	4	56.3391	3.7350	27.9300	0.8280	56.7766	2.1240	50.4251	1.4147	0.7767
49	8	6	60.9010	24.8910	38.4090	1.3440	62.5080	0.1570	36.9320	2.6387	2.6387
41	10	4	55.9875	12.3280	26.8474	0.9220	55.9875	416.3600	52.0474	9.8009	0
61	10	6	83.3481	792.2180	44.5579	1.7500	84.4382	25.8290	46.5400	9.8488	1.3078
49	12	4	76.0640	18.1090	31.3246	1.6250	76.0640	0.2354	58.8180	0	0
73	12	6	83.1798	17204.7970	40.4708	2.2970	84.9211	0.6880	51.3455	4.4978	2.0934
61	15	4	70.8630	31.1720	33.4660	1.0630	70.8630	13.9380	52.7736	0	0
91	15	6	75.5382	2096.2040	42.1599	2.5940	77.6941	0.3265	44.1873	4.6672	2.8540

4.2 Weighted objective function

In order to explore the behavior of model P_1 when the two conflicting objectives have different degree of importance, we adopt a weighted objective function criteria and write the objective function in P_1 as

$$\min_{\{f,x\}} \quad \alpha z + (1-\alpha)\sum_{i \in N} a_i x_i \tag{7}$$

where $\alpha \in [0,1]$. From a practical point view, the weighted objective function in (7) provides an alternative way to handle the trade-off between the total heat generated on patients with more delicate skin versus power energy savings in order to maximize the network lifetime. This would allow to avoid possible hazardous damages on patients. In Table 2,

Table 2: Numerical results for weighted objectives

α	P_1	cpu(s)	LP_1	cpu(s)	Gap$_{LP}$ %
Inst.1: $N=13$, $\#stages=3$ and $nodes/stage=4$					
0	30.8022	0.5780	24.6294	0.4220	20.0400
0.25	24.0651	0.3900	20.1701	0.3600	16.1853
0.5	18.1543	0.4530	14.7102	0.3440	18.9714
0.75	10.5910	0.3900	9.1875	0.3600	13.2519
1	3.5855	0.3750	3.5855	0.5470	0
Inst.2: $N=41$, $\#stages=5$ and $nodes/stage=8$					
0	37.9941	1.1410	35.4446	0.8910	6.7103
0.25	34.7115	2.3280	27.6292	0.9530	20.4034
0.5	28.3399	10.2190	18.9793	0.9530	33.0298
0.75	17.7986	21.2970	10.2668	0.9370	42.3172
1	1.5070	1.1570	1.5070	0.8900	0
Inst.3: $N=49$, $\#stages=8$ and $nodes/stage=6$					
0	49.8155	1.5630	37.1658	0.9370	25.3931
0.25	41.4989	3.8130	29.4254	0.9690	29.0936
0.5	32.2754	17.5310	21.2694	0.9690	34.1004
0.75	20.4248	15.7180	13.1134	0.9540	35.7968
1	4.9574	1.1560	4.9574	1.1400	0

we present preliminary numerical results for different values of parameter α and for three instances having different number of nodes, stages and nodes per stage. More precisely, in column 1 we give the value of α. In columns 2, 3, and 4, 5 we present the optimal function value of P_1 (resp. LP_1) and their cpu time in seconds that CPLEX requires to obtain that solution, respectively. Finally, column 6 shows the gaps for the LP relaxation we compute exactly as in Table 1. Without loss of generality, the input data is randomly generated exactly as for Table1 as well.

From Table 2, we mainly observe that the gaps of the LP relaxation tends to zero when the value of $\alpha \to 1$. This means that solving the LP relaxation of P_1, in this case, suffices to obtain the optimal solution of the problem. On the opposite, when $0 \leq \alpha < 1$, the gaps of its LP relaxation deteriorates considerably which turns the problem more difficult to solve.

In order to provide more insight regarding our VNS approach, we further present average numerical results for the instances presented in Table 1. These results are presented in Table 3 and the column information is exactly the same as for Table 1. We generate 50 samples for the input data of the instances in rows 1-13 while for the instances in rows 14-16 we use only 10 samples to compute the averages as their cpu times become highly prohibitive. In particular, we arbitrarily set the maximum time for CPLEX to solve these instances be at most 3600 seconds. From Table 3, we observe similar trends as in Table 1 concerning the gaps obtained with VNS. They are not larger than 3.5 % for all the instances we test when compared to the optimal solution of the problem. We also see that the cpu times required by the VNS approach are larger than those required by CPLEX for instances in rows 1-9 while for instances in rows 10-16, CPLEX requires more cpu time. In particular, the instances in rows 14-16 require a huge amount of cpu time using CPLEX while the VNS approach finds very tight near optimal solutions with gaps no larger than 2% in less than 25 seconds approximately. Another observation is that the initial solutions obtained with VNS approach are not feasible for instances in rows 1-8. Which means at least in one of the samples, the ini-

Table 3: Average numerical results for the VNS approach

N	# stages	nodes/stage	P_1	cpu(s)	LP_1	cpu(s)	VNS	cpu(s)	Gap_{LP} %	Gap_{VNS}^{Ini}%	Gap_{VNS}%
13	3	4	39.8464	0.4312	32.0752	0.4062	39.8464	0.9370	19.6396	-	0
46	3	15	95.0189	3.4718	80.4871	1.7472	95.7131	110.3312	15.2916	-	0.5546
61	3	20	152.7756	7.9654	129.0012	3.8741	153.9987	477.3697	16.2044	-	1.1142
17	4	4	42.2965	0.4716	32.9802	0.3938	42.2965	9.4488	22.1685	-	0
61	4	15	96.7648	17.4686	80.2268	2.8404	98.8593	252.7788	17.0192	-	2.2219
21	5	4	45.2427	0.6064	32.5676	0.4186	45.2427	26.4560	26.9386	-	0
41	5	8	72.1552	10.3562	52.7956	0.9094	74.8638	36.1282	27.0548	-	3.1426
51	5	10	85.3136	38.3716	65.2315	1.5314	87.1930	42.5282	23.5664	-	2.9688
33	8	4	58.1523	2.5686	31.7155	0.5250	58.7456	10.6092	46.3102	4.0809	1.3087
49	8	6	69.7592	82.4720	46.7561	1.0534	71.0608	17.0594	33.0253	9.5012	1.8658
41	10	4	63.9525	10.1404	37.6166	0.6188	65.2207	7.5086	40.8058	3.7043	2.0128
61	10	6	68.0209	100.3878	40.9167	1.3532	70.3692	47.8566	40.1894	8.8179	3.2827
49	12	4	66.3268	30.0688	29.9523	0.7094	67.0870	0.1336	54.8053	4.1534	1.7767
73	12	6	75.0030	3456.5126	44.3070	1.8002	76.2619	16.2030	40.9237	5.2012	1.9912
61	15	4	72.5088	1441.3000	35.3752	0.9186	72.7524	12.2218	50.7315	1.0480	0.2773
91	15	6	80.5427	2740.1874	44.6374	2.6750	81.0830	20.6280	44.8002	3.2151	0.8021

-: No feasible initial solution found.

tial solution was infeasible. Conversely, finding initials solutions for instances in rows 9-16 is easier. In general, the gaps of the initial solutions are not larger than 10%. Finally, the gaps obtained with the LP relaxation of P_1 are not tight when compared to the optimal solution of the problem. In general, we note that the LP gaps deteriorate significantly when the number of stages is larger than the number of nodes per stage which is the case for instances in rows 9-16.

5 CONCLUSIONS

In this paper, we proposed a minmax multicommodity netflow formulation to optimally route data packets in a healthcare wireless body area network. The aim of the model is to minimize the worst power consumption of each bio-sensor node over the body of a patient plus the total heating costs subject to flow conservation and maximum capacity energy constraints. The model is formulated as a mixed integer linear program. Thus, we proposed a variable neighborhood search metaheuristic procedure to obtain near optimal solutions. Preliminary numerical results indicate that the VNS approach obtains near optimal solutions with integrality gaps no larger than 3.5%. As future work, we plan to consider other layout configurations while using more realistic data, and new algorithmic procedures to solve efficiently the LP relaxations within each iteration of the VNS approach.

ACKNOWLEDGEMENTS

The author Pablo Adasme is grateful for the financial support given by Conicyt Chilean government through the Insertion project number: 79100020.

REFERENCES

Ababneh, N., Timmons, N., and Morrison, J. (2012a). Ebrar: Energy-balanced rate allocation and routing protocol for body area networks. *In IEEE Symposium on Computers and Communications, ISCC 2012*, pages 475–478.

Ababneh, N., Timmons, N., Morrison, J., and Tracey, D. (2012b). Energy-balanced rate assignment and routing protocol for body area networks. *In 26th International Conference on Advanced Information Networking and Applications Workshops, WAINA 2012*, pages 466–471.

Abouzar, P., Shafiee, K., Michelson, D., and Leung, V. (2011). Action-based scheduling technique for 802.15.4/zigbee wireless body area networks. *In IEEE 22nd International Symposium on Personal Indoor and Mobile Radio Communications, PIMRC 2011*, pages 2188–2192.

Arrobo, G. and Gitlin, R. D. (2011). New approaches to reliable wireless body area networks. *In IEEE International Conference on Microwaves, Communications, Antennas and Electronics Systems, COMCAS 2011*, pages 1–6.

Awad, A., Mohamed, A., and El-Sherif, A. (2013). Energy efficient cross-layer design for wireless body area monitoring networks in healthcare applications. *In IEEE 24th International Symposium on Personal, Indoor and Mobile Radio communications: MAC and Cross-Layer Design Track.*

Deb, K. (2002). Multi-objective optimization using evolutionary algorithms. *Wiley and Sons*.

Elias, J. and Mehaoua, A. (2012). Energy-aware topology design for wireless body area networks. *In IEEE International Conference on Communications, ICC 2012*, pages 3409–3410.

Fang, G. and Dutkiewicz, E. (2009). Bodymac: Energy efficient tdma-based mac protocol for wireless body area networks. *In 9th International Symposium on Communications and Information Technology, ISCIT 2009*, pages 1455–1459.

Glover, F. and Kochenberger, G. A. (2003). Handbook in metaheuristics. *International Series in Operations Research and Management Science, Kluver Academic Publishers, Springer 2003*, 57:556.

Hansen, P. and Mladenovic, N. (2001). Variable neighborhood search: Principles and applications. *European Journal of Operational Research*, 130:449–467.

Hansen, P., Mladenovic, N., and Perez-Brito, D. (2001). Variable neighborhood decomposition search. *Journal of Heuristics*, 7:335–350.

Huang, C., Liu, M., and Cheng, S. (2010). Wrap: A weighted random value protocol for multiuser wireles body area networks. *In IEEE International Symposium On Spread Spectrum Techniques and Applications, ISSSTA 2010*.

Jourdan, B. and de Weck, O. (2004). Layout optimization for a wireless sensor network using a multi-objective genetic algorithm. *In: IEEE Semiannual Vehicular Technology*, 5:2466–2470.

Kinsella, K. and Phillips, D. (2005). Global aging. *The challenge of success, Population Bulletin*, 60.

Kwak, K. S., Ameen, M. A., Kwak, D., and Lee, C. (2009). A study on proposed ieee 802.15 wban mac protocols. *In 9th International Symposium on Communications and Information Technology, ISCIT 2009*, pages 834–840.

McFadden, T. and Indulska, J. (2004). Context-aware environments for independent living. *In: 3rd National Conference of Emerging Researchers in Ageing*, pages 1–6.

Perkins, C. E. and Royer, E. M. (1999). Ad-hoc on-demand distance vector routing. *In IEEE Second Workshop on Mobile Computing Systems and Applications*, pages 90–100.

Reusens, E., Wout, J., Latre, B., Braem, B., Vermeeren, G., Tanghe, E., Martens, L., Moerman, I., and Blondia, C. (2009). Characterization of on-body communication channel and energy efficient topology design for wireless body area networks. *IEEE Transactions on Information Technology in Biomedicine*, 13(6).

Schmidt, A. and Laerhoven, K. (2001). How to build smart appliances ? *IEEE Personal Communications*, 8(4):66–71.

Shi, X., Medard, M., and Lucani, D. (2011). When both transmitting and receiving energies matter: An application of network coding in wireless body area networks. *In Networking 2011 Workshops, Lectures Notes in Computer Science*, 6827:119–128.

Stanford, V. (2002). Using pervasive computing to deliver elder care. *IEEE Pervasive Computing*, 1(1):10–13.

Tang, Q., Tummala, N., Gupta, S., and Schwiebert, L. (2005). Scheduling to minimize thermal effects of implanted biosensor networks in homogeneous tissue. *IEEE Transactions on Biomedical Engineering*, 52(7):1285–1294.

Ullah, S., Bin, S., Islam, S., Pervez, K., Saleem, S., and Kwak, K. (2010). A study of mac protocols for wbans. *Sensors*, 10(1):128–145.

Ullah, S., Higgins, H., Braem, B., Latre, B., Blondia, C., Moerman, I., Saleem, S., Rahman, Z., and Kwak, K. S. (2012). A comprehensive survey of wireless body area networks on phy, mac, and network layers solutions. *Journal of Medical Systems*, 36:1065–1094.

Watteyne, T., Augfie-Blum, S., Dohler, M., and Barthel, D. (2007). Anybody: a self-organization protocol for body area networks. *In: Second International Conference on Body Area Networks (BodyNets)*, pages 11–13.

Yan, Z., Liu, B., and Chen, C. W. (2012). Qos-driven scheduling approach using optimal slot allocation for wireless body area networks. *In IEEE 14th International Conference on e-Health Networking, Applications and Services, Healthcom 2012*, pages 267–272.