A Multi-Objective Routing Algorithm for Wireless Multimedia Sensor Networks

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Abstract

In this paper a new multi-objective approach for the routing problem in Wireless Multimedia Sensor Networks (WMSNs) is proposed. It takes into account Quality of Service (QoS) requirements such as delay and the Expected Transmission Count (ETX). Classical approximations optimize a single objective or QoS parameter, not taking into account the conflicting nature of these parameters which leads to sub-optimal solutions. The case studies applying the proposed approach shows clear improvements on the QoS routing solutions. For example, in terms of delay, the approximate mean improvement ratios obtained for scenarios 1 and 2 were of 15 and 28 times, respectively.

Keywords: Multi-Objective Optimization, Wireless Multimedia Sensor Networks, Strength Pareto Evolutionary Algorithm, Quality of Service.

1. Introduction

Wireless Sensor Networks [1] are composed of small devices, called sensor nodes, which cooperate to forward collected data to a sink node that either

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uses the data locally or forwards it to other networks through a gateway, like for example, the Internet. Sensors are resource-limited devices composed of sensing, processing, transceiver, and power units.

The addition of low cost multimedia hardware to sensors fostered the development of Wireless Multimedia Sensor Networks [2], allowing the retrieval of multimedia streams, and/or scalar sensor data. Wireless sensor networks have many application areas [2] such as multimedia surveillance sensor networks, storage of potentially relevant activities, traffic avoidance, enforcement and control system, and many more.

Routing protocols [3] in WSNs can be classified according to the network structure, protocol operation, how routing information is acquired and maintained. In terms of network structure, routing protocols can be divided into flat-based routing, hierarchical-based routing and location-based routing. In flat-based routing, typically nodes have similar roles, whereas in hierarchical-based routing nodes have different roles. In location-based routing, location information is used to route data in the network. According to protocol operation, these protocols can be classified as multipath-based, query-based, negotiation-based, QoS-based, or coherent-based routing techniques. In multipath-based routing, multiple paths are maintained between a source-destination pair. In query-based routing, the destination node sends a query through the network and the node with this data, sends an answer. In negotiation-based routing, high level data descriptors are used to eliminate redundant data transmissions through negotiation. In QoS-based routing, certain QoS metrics have to be satisfied while routing data through the network. In coherent-based routing, sensors cooperate in processing data flooded throughout the network. According to how routing information is acquired and maintained, they can be classified into proactive, reactive, and hybrid. In proactive protocols, nodes compute routes before they are needed. In reactive protocols, nodes compute route on demand. Hybrid protocols combines ideas of both.

Multimedia applications have different QoS requirements such as, bounded latency or delay, throughput, jitter, availability, and energy consumption. Since energy efficiency is considered as the main goal of most WSNs routing protocols, the majority of these protocols does not perform well when applied to QoS-constrained WMSN. Routing techniques in WMSN can be classified similarly to those of WSNs. In [4] another categorization for WMSN routing protocols is presented. Protocols are classified based on the handled data types, data delivery model types, classes of algorithms adopted, and the used hole-bypassing approach.

Many routing schemes [4, 5] have been proposed to address QoS requirements. In most of these schemes, only one of the desired objectives is optimized, while others are assumed as problems' constraints [6]. In certain applications, a meta-heuristic approach [7, 8] using a Multi-objective Optimization (MO) algorithms that can provide several optimal solutions may be preferred, since single design objective algorithms ignore other relevant objectives. By considering all objectives simultaneously, a set of optimal solutions can be generated, also known as the Pareto solutions [9] of the multi-objective problem. It is also known from [10] that finding optimal routes for multiple objectives in networks (multi-constrained QoS routing), is a NP-Complete problem, hence efficient heuristic search algorithms based on reduced-complexity Evolutionary Algorithms (EAs) [11] are necessary.

The Expected Transmission Count (ETX) [12] metric is an estimation of the expected total number of transmissions (including retransmissions) required to deliver a packet to the destination node successfully. ETX allows finding high throughput paths on a multi-hop wireless network, and incorporates the effects of link loss ratios, asymmetry in the loss ratios between the two directions of each link, and the interference among the successive links of a path.

This paper proposes a new multi-objective approach for the WMSN routing problem that takes into account QoS parameters such as delay and ETX. A comparison of the proposed approach with two alternative routing protocols was also presented.

The rest of this paper is organized as follows. Section 2 discusses related work. Section 3 presents the WMSN routing problem formulation. Section 4 presents the Multi-objective optimization concept, formulation and our Strength Pareto Evolutionary Algorithm (SPEA) implementation used to solve the problem. Sections 5 and 6 present the simulation model and results respectively. Finally, Section 7 presents conclusions and future work.

2. Related Work

The Dynamic Source Routing (DSR) [13] protocol, one of the well known Mobile Ad-hoc Networks (MANETs) routing protocols, is a single path on-demand routing protocol. If a data packet has to be sent and no route to the destination is available, the source node starts a route discovery process by flooding Route REQuest (RREQ) packets targeting the destination node. Each neighbor receiving the RREQ packet checks if it is the destination. If so, it sends a Route REPly (RREP) packet back to the source after adding the accumulated routing information contained in the RREQ packet. The shortest returned path is the one used for routing.

The High Throughput Low Coupling Multipath extension to the Dynamic Source Routing (HTLC-MeDSR) [14] protocol is a multipath on-demand routing protocol. Similarly to DSR, a RREQ is issued only if a data packet has to be sent and no route to that destination exists. The destination also issues RREP packets to the received RREQ packets. HTLC-MeDSR uses probe packets to detect link failures and each node overhears other nodes packet transmissions to increase the False Routing Failures (FRFs) accuracy. HTLC-MeDSR uses ETX information to find high throughput paths, and the correlation factor to find paths with low coupling if they exist. The set of paths with the highest throughput and the small correlation factor are the ones used.

The authors of [15] proposed a multi-objective routing algorithm that identifies a set of Pareto Optimal routes, which represent different trade-offs between energy consumption and communication latency, for both single and multipath routing problems. One of the reasons behind the selection of the objectives is that sensor nodes are powered by batteries which makes power conservation an important goal. By minimizing the number of hops in a path, communication latency can be minimized since in most situations, latency is a consequence of the number of intermediate nodes along a communication path. WSN and WMSN have different QoS requirements, as multimedia traffic generally requires a minimum bandwidth.

In [16], a performance comparison of two Multi-Objective Evolutionary Algorithms (MOEA), namely the Non-dominated Sorting based Genetic Algorithm-II (NSGA-II) and the Multi-Objective Differential Evolution (MODE) algorithm, is presented. MOEAs are used to find optimal routes between a source and a destination nodes taking into account conflicting objectives, like dissipated energy and end-to-end delay in a fully-connected wireless network. Since sensors can be deployed over a vast area, fully-connected networks were not considered in this study.

The closest work to ours was presented in [17]. The authors propose a QoS based Multi-Objective Optimization algorithm aiming at ensuring certain QoS levels in Wireless Mesh Networks (WMN). Some of the QoS parameters optimized are bandwidth, packet loss rates, delay and power consumption. Our approach targets WMSN QoS requirements instead. The ETX metric is used since it allows finding high throughput paths taking into account link loss ratios, links' asymmetries, and interference among the successive links of a path. The authors in [14] have shown that low ETXs paths are also energy efficient. The selection of a link with a certain bandwidth does not guarantee that the path has a good throughput. Another difference was on the problem formulation presented. The authors of [17] presented a linear programming formulation, not making clear how the presented formulation is used by the multi-objective optimization algorithm. We modeled the routing problem as a multi-constrained QoS routing problem and consequently used multi-objective optimization algorithms to solve it. In addition, in [17], it was not clear how the MOEA algorithm was implemented. In contrast, we present and explain in detail how our MOEA algorithm was implemented, namely: (1) the population initialization process, (2) how genetic operators were used.

Table 1: Summary of related work

Publication	MOEA algorithm	Scenarios considered	Metrics considered
[15]	MODE	Wireless Sensor Network	Energy consumption, delay
[16]	MODE, NSGA-II	Full-connected network	Energy consumption, delay
[17]	NSGA-II	Wireless Mesh Network	Bandwidth, packet loss, energy consumption and delay
[18]	RVGA	Wireless Mesh Sensor Network	Energy consumption, battery lifetime

The authors of [18] proposed a multi-objective routing optimization approach that uses a real-valued genetic algorithm (RVGA), which obtain benefits of better convergence properties by maintaining an unconstrained Pareto archive without employing an independent search population, aiming at prolonging the average network lifetime. The proposed approach, whose objectives are to minimize the total energy consumption, and to maximize the time required for nodes to recharge or replace their batteries, accomplishes its goal by combining a k-shortest paths based search space pruning and an edge metric consisting of an association between a pair of nodes energy cost with its link. Energy efficient routing protocols are important as they prolong nodes battery lifetime. Routing protocols that use the ETX metric can find energy efficient paths, which allow the overall reduction of the networks energy consumption.

Table 1 provides a summary of related multi-objective optimization work based on MOEA algorithms used, scenarios considered and the metrics used as objective functions.

3. Problem Formulation

The notation and terminology used is borrowed from [19]. A Wireless Multimedia Sensor Network can be represented by a connected graph $G(V, E)$ where V is the set of vertices representing nodes and E is the set of edges representing links between the nodes. Each edge $e = u \rightarrow v$ is associated with k weights where $\omega_l(e) > 0, \forall e \in E$ and $1 \leq l \leq k$. Similarly to [19], it is assumed that all constraints are path constrains, and that the weight of a path is equal to the sum of the weights of all edges on the path. Thus, for each path $p = v_0 \to v_1 \to \cdots \to v_n, \omega_l(p) = \sum_{i=1}^{n} \omega_l(v_{i-1} \to v_i)$. A path constraint, e.g., delay, represents the end-to-end QoS requirement for the complete path.

Definition 3.1. Multi-constrained QoS routing problem. Given an undirected graph $G(V, E)$ with each edge e is associated with k weight functions where $\omega_l(e) > 0, \forall e \in E$ and $1 \leq l \leq k$. A constants vector $c = (c_1, c_2, , c_k)$. A multi-constrained QoS routing problem consists in finding a path p between a source s and destination d, so that, $\omega_l(p) \leq c_l$, where $1 \leq l \leq k$.

Definition 3.2. Multi-constrained Optimal QoS routing problem. Given an undirected graph $G(V, E)$ with each edge e is associated with k weight functions where $\omega_l(e) > 0, \forall e \in E$ and $1 \leq l \leq k$ and a path $p = v_0 \to v_1 \to \cdots \to v_n$ is considered an optimal QoS path from s to d, if $\exists q = s \to \cdots \to d$ such that $\omega(q) < \omega(p)$.

Each optimal path can possibly satisfy a particular QoS constraint not yet satisfied by any other path. QoS routing guarantees finding a path that satisfies the QoS constraints if it exists, by considering all QoS optimal paths. The number of optimal paths can grow exponentially with respect to the network size [19].

The WMSN QoS routing problem can be addressed meta-heuristically using multi-objective optimization algorithms, as explained in the following section.

4. Multi-Objective Optimization

4.1. Basic Definitions

Multi-objective Optimization Problems (MOP) deals with more than one objective function which are to be minimized or maximized, subject to a number of constraints:

$$
\left.
\begin{array}{ll}
\text{Minimize/Maximize } f_m(x), & m = 1, 2, ..., M; \\
\text{subject to } g_j(x) \geq 0, & j = 1, 2, , J; \\
h_k(x) = 0, & k = 1, 2, , K; \\
x_i^{(L)} \leq x_i \leq x_i^{(U)} & i = 1, 2, , n.
\end{array}
\right\} \tag{1}
$$

where, M is the number of objective functions subject to J inequalities and K equality constraints. A solution x is a vector of n decision variables. The lower bound $x_i^{(L)}$ and upper bound $x_i^{(U)}$, restricting each decision variable x_i, constitute a decision variable space D. L and U are the Lower and Upper bounds restricting each decision variable.

A *feasible solution* x[1] is one that satisfies all constraints and decision variable bounds. The set of all feasible solutions is called the *feasible region* (or *search space* S).

Definition 4.1. Domination. A solution $x^{(1)}$ is said to dominate another solution $x^{(2)}$, if the following conditions are verified:

1. $x^{(1)}$ is not worse than $x^{(2)}$ in all objectives, or $f_m(x)^{(1)}$ is not worse than $f_m(x)^{(2)}$ for all m=1,2,3,M.
2. $x^{(1)}$ is strictly better than $x^{(2)}$ in at least one objective, or $f_{\overline{m}}(x^{(1)})$ is better than $f_{\overline{m}}(x^{(2)})$ for at least one $\overline{m} = 1, 2, 3, ..., M$.

Definition 4.2. Non-dominated set. For a set of solutions P, a non-dominated set of solutions $\overline{P}$ is a set of solutions that are not dominated by any member of the set P.

Definition 4.3. Globally Pareto-Optimal set. A Globally Pareto-Optimal set is a non-dominated set of the entire feasible search space S. Since solutions of the globally Pareto-optimal set are not dominated by any other within the search space, they are optimal solutions of the MOP, and are simply referred as the Pareto-optimal set (POS).

[1] A vector of n decision variables $(x_1, x_2, ..., x_n)^T$ constitutes a solution x

4.2. MOP Formulation

The multi-objective optimization algorithms goal is to produce a diverse set of optimal solutions that can be used by the user while evaluating trade-offs between different objectives.

4.2.1. Objective Functions

The goal is to minimize the following metrics: delay and ETX.

Delay. In computer networks [20], a packet originated in a source node passes through a set of intermediate nodes, until it reaches its destination node. During its travel from one node to a subsequent one along a path, the packet suffers, at each node, from several types of delays, namely nodal processing delay, queuing delay, transmission delay, and propagation delay. Processing delay (d_{proc}) can be seen as the time required (1) to examine the packets header in order to decide where to direct the packet, and/or (2) to check the packet for bit-level errors that possible occurred while transmitting it to a subsequent node. Queueing delay (d_{queue}) corresponds to the delay packets suffer in nodes queues while waiting to be transmitted onto the link. Transmission delay (d_{trans}) is the amount of time necessary to transmit all of the packets bits into the link. Propagation delay (d_{prop}) is the time necessary for all packets bits to propagate from the beginning of a link of a given node to the subsequent one. The packets bits propagate at the propagation speed of the link, which depends on type of physical medium of the link. The propagation speed is in the range from $2 \cdot 10^8$ to $3 \cdot 10^8$ $meters/sec$. So, the nodal delay is defined as

$$delay = d_{proc} + d_{queue} + d_{trans} + d_{prop} \tag{2}$$

$$d_{trans} = \frac{L}{R} \tag{3}$$

$$d_{prop} = \frac{d}{s} \tag{4}$$

where L is the packet length in $bits$, R is the link transmission rate in $bits/sec$, d is the distance among nodes in $meters$, s is the link propagation speed in *meters/sec.*

Since wireless networks are composed of many nodes, the total delay (d_{total}), also called end-to-end delay, considering that there are $K1$ intermediate nodes between a source node and a destination node, is given by

$$d_{total} = \sum_{i=1}^{K} delay_i \quad (5)$$

where K is the number of hops in the end-to-end path.

Expected Transmission Count. The Expected Transmission Count (ETX) [12] metric is the expected total number of transmissions (including retransmissions) required to deliver a packet to the destination node successfully. ETX allows finding high throughput paths on a multi-hop wireless network, and incorporates the effects of link loss ratios, asymmetry in the loss ratios between the two directions of each link, and the interference among the successive links of a path.

In order to compute the ETX of a link, the link quality (LQ) and the neighbor link quality (NLQ) are used. The link quality (LQ) can be seen as the measured probability that data packet originated at a given node (e.g., A) successfully arrives at a subsequent node (e.g., B). The neighbor link quality (NLQ) is a measure of the quality of the link in the opposite direction, i.e., how many of data packets that were sent from B are received by A.

The probability that a data packet is successfully sent to a neighbor and, on receiving it, the neighbor successfully replies with a response data packet is $LQ \times NLQ$. Since each attempt to transmit a packet can be considered a Bernoulli trial, the expected number of transmissions is given by

$$ETX = \frac{1}{LQ \times NLQ} \quad (6)$$

Considering that there are $K1$ intermediate nodes between a source-destination pair, the total ETX is the sum of the ETX metrics along the path, i.e.,

$$ETX_{total} = \sum_{i=1}^{K} ETX_i. \quad (7)$$

where K is the number of hops in the end-to-end path.

4.2.2. Constraints

Path Constraint. WMSN applications have different QoS requirements (Q) such as bounded latency (or delay) L, bandwidth (or throughput) B, jitter J, packet loss P and energy consumption E, so $\{L, B, J, P, E\} \subset Q$. Depending on the constraints, and in order to impose them it is necessary to check whether $min\{\omega_Q(p)\} \geq Q_{min}$ or $max\{\omega_Q(p)\} \leq Q_{max}$, where Q_{min} or Q_{max} are the minimum or maximum values allowed. For example, the bandwidth path constraint ensures that $min\{\omega_B(p)\} \geq B_{min}$, for all valid paths.

4.3. Strength Pareto Evolutionary Algorithm

The Strength Pareto Evolutionary Algorithm (SPEA) [9] is an elitist multi-objective evolutionary algorithm (MOEA) since it ensures that good solutions found in early runs are only replaced if better solutions are discovered. The algorithm achieves it by maintaining an external population $\overline{P}_l$ consisting of a fixed number of non-dominated solutions found before the beginning of the simulation. If new non-dominated solutions are found during the simulation, they are compared with the existing external population and the resulting non-dominated solutions are stored. The external population participates in the genetic operators with the current population expecting to influence the population towards good regions of the search space. Below one iteration of the algorithm step-by-step is described [9]. Initially, a population P_0 of size N is randomly created, and the external population $\overline{P}_0$ with maximum capacity of $\overline{N}$ is empty. In generation t,

Step 1. Find the best non-dominated set of P_t and copy these solutions to $\overline{P}_t$.
Step 2. Find the best non-dominated solutions of the modified population $\overline{P}_t$ and delete all dominated solutions.

Figure 1: Solution representation.

Step 3. If $|\overline{P}_t| \geq \overline{N}$, the clustering technique must be used to reduce the external population size to $\overline{N}$. If not, do nothing to $\overline{P}_t$. The outcome is the external population $\overline{P}_{t+1}$ used in the next generation.

Step 4. Assign fitness to each elite solution $i \in \overline{P}_{t+1}$ and to each population member $j \in P_t$.

Step 5. In a minimization sense and with the previously assigned fitness values, apply binary tournament selection, crossover and mutation operators in order to create the new population P_{t+1} of size N using the combined population $(\overline{P}_{t+1} \cup P_t)$ of size $(\overline{N} + N)$.

The new external and current population that are used in the next generation, are obtained through steps 3 and 5 respectively. When the stopping criteria is satisfied, the algorithm stops.

4.4. SPEA Implementation

A MOEA consists of the individual, the set of individuals also called population, the fitness of each individual and of the genetic operators applied to the population. Below a description is given on how each of the components is obtained:

4.4.1. Individual

Each candidate solution (individual or chromosome) represents a path between a source node SN and a destination node DN. A link connects two consecutive nodes in a path (see Figure 1). For example, Figure 4a (Section 5.1) shows a simulation scenario with 49 nodes. The source node is node 0 and the destination node is node 48. Figure 2 shows a candidate solution (marked on Figure 4a) for scenario 1.

0	8	22	30	38	40	48

Figure 2: A candidate solution for scenario 1.

4.4.2. Population Initialization

The initial population is created using the Breadth First Search (BFS) [21] graph search algorithm. It was previously mentioned that HTLC-MeDSR uses probe packets to determine ETX. A simulation with the HTLC-MeDSR routing protocol was performed on NS-2[2] [22] network simulator without any traffic source and all links ETX and delay values were collected. The probe packet size was set to 2312 bytes[3], in order to measure the maximum transmission time. BFS algorithm was fed with all links so that it could compute a set of individuals. Since BFS explores all possible nodes and links among nodes, its time complexity is $O(|V| + |E|)$. Consequently, the BFS execution time depends on the networks size [21], i.e., the number of nodes and links, which is significant for large networks. To speed up the search process, each branch was probabilistically explored with a probability of 20% and 1% for scenarios 1 and 2 respectively (see Section 5.1). Thus, the search algorithm was not exhaustive, and the feasible individuals were found using MOEA's genetic operators, i.e., crossover and mutation, to solve the problem as explained in the following subsections. The initial population is randomly selected from the sets of individuals obtained for both scenarios.

4.4.3. Fitness Assignment

Fitness values are assigned to each individual of the initial population using the ETX and delay values collected in the previous step. An individuals ETX is the sum of its links ETX values. An individuals end-to-end delay is the sum of its links delay values. The set of non-dominated individuals is selected taking

[2]http://www.isi.edu/nsnam/ns/

[3]the maximum IEEE 802.11 [23] frame body size

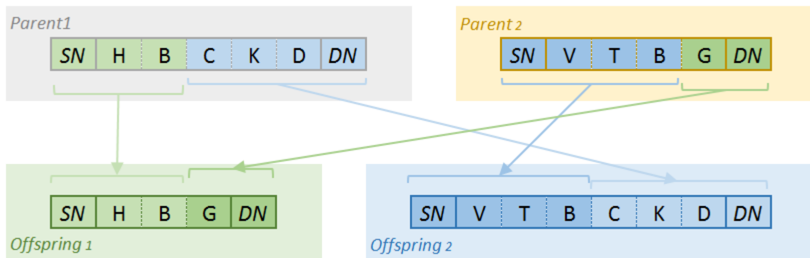


Figure 3: During the crossover operation, $offspring_1$ and $offspring_2$ are created by concatenating parts from $parent_1$ and $parent_2$. For example, $offspring_1$ results from the concatenation of nodes starting from SN to common node B from $parent_1$ and with the nodes following B to DN in $parent_2$.

into account the individual's fitness values.

4.4.4. Genetic Operators

The goal of applying genetic operators is to produce better solutions than the current ones.

Selection Operator. The best individual found in the binary tournament selection is placed in the mating pool. The binary tournament selection is applied to all population in two rounds, so that each individual participates at most twice in the two tournaments. Therefore, the offspring is created from the best individuals (parents) which are chosen 'only' from the mating pool.

Crossover Operator. A single-point crossover with a crossover probability P_C was considered. The algorithm first checks the crossover probability to determine if crossover will take place. Then, the algorithm tries to obtain a crossover node by randomly selecting a position after the source and prior to the destination node, taking into account the size of the shortest path (see Figure 3). If no common node exists, a crossover point is randomly selected. If the crossover node is common between the parents, there is a high probability of producing valid offspring.

Mutation Operator. The algorithm checks the mutation probability P_m to determine if mutation shall take place. Then the algorithm randomly obtains a mutation position after the source and prior to the destination node. The segment between the source node s and the node at the mutation position is kept, and the BFS algorithm is applied to find valid nodes until the destination node. So, the algorithm enables population diversity.

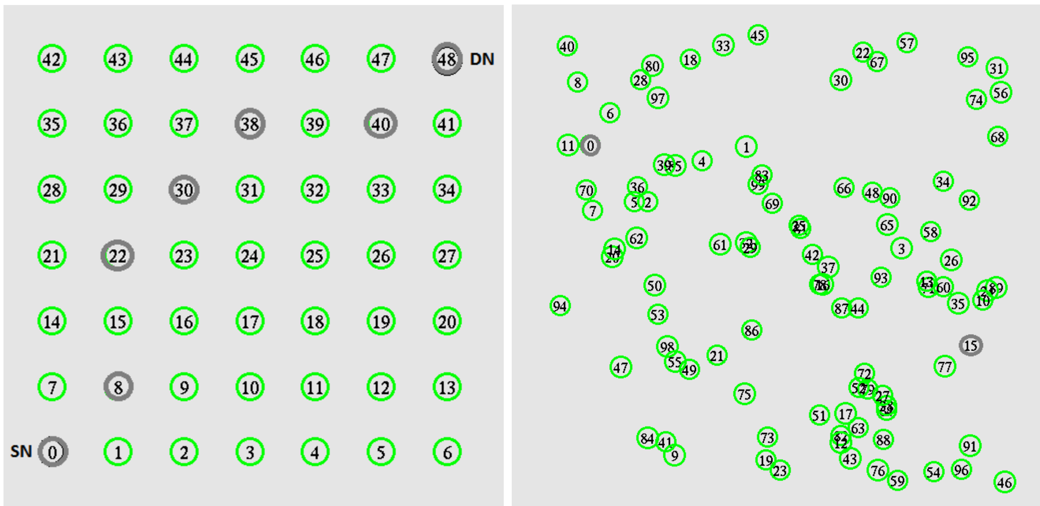
5. Simulation Model

The simulation model evaluation objective is twofold. On the one hand, a simulation with NS-2 was performed aiming at obtaining delay and ETX values for each edge (or link) in the network. Besides that, simulations with DSR and HTLC-MeDSR were also performed, and the total delay and ETX values of the paths used by the algorithms were obtained, as will be explained in section 6. On the other hand, the proposed SPEA was evaluated.

5.1. Network Simulator Setup

A simulation model based on NS-2 was used together with two different network scenarios (see Figure 4). Scenario 1 is a grid network with 49 nodes regularly distributed over an area of 500m x 500m. In scenario 2, 100 nodes are randomly distributed over an area of 700m x 700m. Here, only static scenarios were considered since they are more common in WMSN [14]. There is only one source-destination pair which is placed at opposite corners. The simulation duration is of 200s. Ten simulation runs were executed and the results statistically analyzed. In order to get non-deterministic results across runs, different seeds were used. One simulation traffic source was used: Constant Bit Rate (CBR) at 128kbps. The packet size is set to 2312bytes. The mobile hosts channel capacity varied between 6, 12, 24 and 54Mbps depending on the distance between the nodes, as for any Wi-Fi link. Higher transmission rates for shorter distances. The transmission range is the same for all transmitters. The IEEE 802.11 distributed coordination function (DCF) was used for Wireless LANs and, finally, the 802.11Ext [24] was considered as NS-2s MAC protocol.

Table 2 shows the simulation parameters.



(a) Scenario 1

(b) Scenario 2

Figure 4: The simulation scenarios.

5.2. SPEA Setup

Table 3 shows the SPEA parameters. Fifteen runs of the proposed SPEA were performed.

6. Simulation Results

The proposed algorithm was compared with two routing protocols, respectively:

- *DSR*: Dynamic Source Routing which is a single path routing protocol.
- *HTLC-MeDSR*: High Throughput Low Coupling Multipath Extension to the Dynamic Source Routing (HTLC-MeDSR) protocol which is a multipath routing protocol that uses ETX and CF.

6.1. Non-dominated Sets

Figure 5 presents all solutions (dominated and non-dominated) obtained over fifteen runs of the proposed algorithm on both scenarios. In scenario 1, 80%

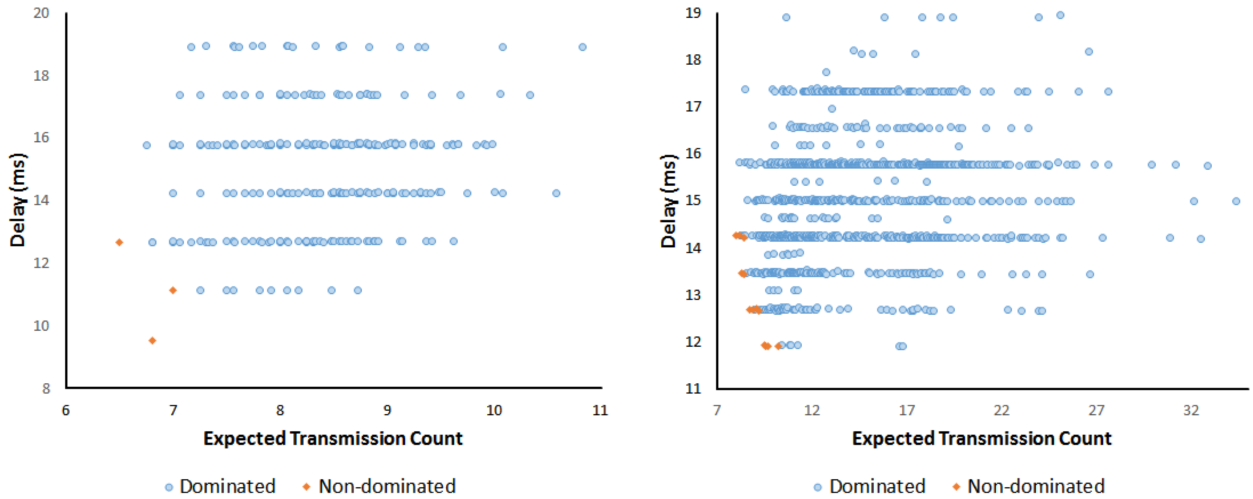
Table 2: Simulation Parameters

	Scenario 1	Scenario 2
Network field	550m x 550m	700m x 700m
Number of Sensor	49	100
Number of Sinks/Number of Sources	1/1	
Source Node (SN)	0	0
Destination/Sink Node (DN)	48	15
Packet Size	2312 bytes	
Radio Propagation Model	Two Ray Ground	
Source Data rate	128 Kbps	
Traffic type	CBR	
MAC Layer IEEE	802.11a	
Physical Layer data rate	6, 12 Mbps	6, 12, 24, 54 Mbps
Simulation time	200 seconds	

of the non-dominated solutions (see Figure 5a) presented the following pairs of values: (6.5, 12.66) and (6.81, 9.54), for (ETX, Delay) respectively. In scenario 2, the non-dominated sets were close but not overlapping. This was due to the increase in network dimension and the use of a random network topology in comparison to the grid topology of scenario 1.

Table 3: SPEA Parameters

	Scenario 1	Scenario 2
Population Size	100	200
External Population Size	3	
Number of Generations	20	50
Crossover probability (P_C)	0.75	
Mutation Probability (P_m)	0.2	



(a) Scenario 1

(b) Scenario 2

Figure 5: Non-dominated Sets.

Table 4: Maximum transmission times

Data rates (Mbps)	Txtime (ms)
6	3.15
12	1.59
24	0.80
54	0.41

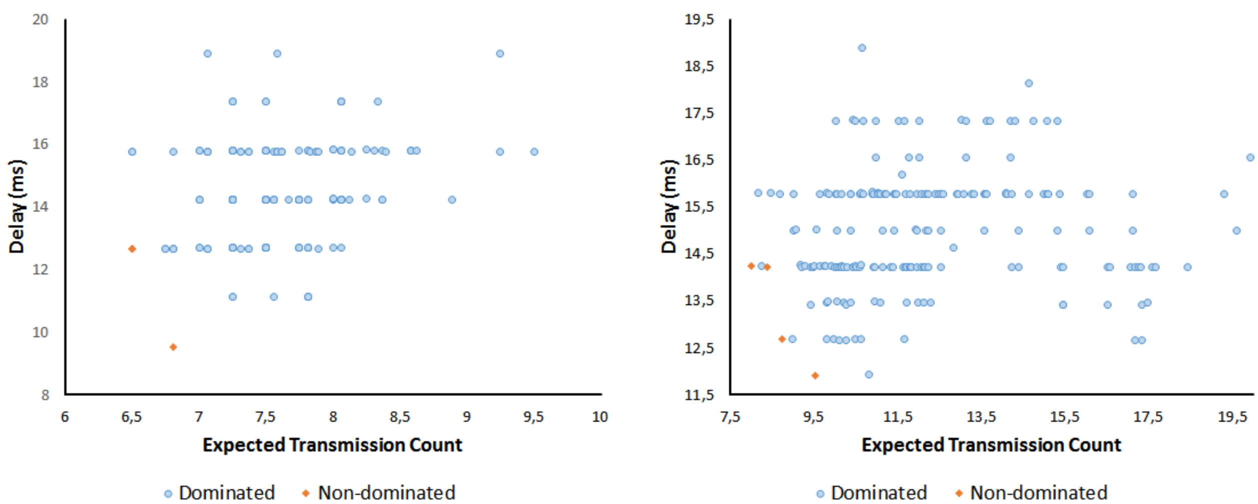
6.2. Pareto-optimal Sets

Table 4 shows the maximum amount of time necessary to transmit a data packet among nodes, for each one of the physical layer data rates presented on Table 2. The end-to-end delay values presented on Figure 6 and Table 5 are discrete because of all possible combinations of transmission time values presented on Table 5.

The Pareto-optimal Sets (POSs) for scenarios 1 and 2 are composed of 5 and 4 optimal solutions respectively (see Figure 6). The corresponding ETX and end-to-end delay values of all optimal solutions are listed in Table 5. In terms of the multi-objective optimization, two distinct goals should be considered: (1) solutions should be as close as possible to the POS, and (2) solutions should be

Table 5: Optimal solutions for the proposed SPEA

Scenario	Solutions	Objective Functions	
		ETX	Delay (ms)
1	[0,2,10,18,26,34,48]	6.5	12.66
	[0,8,16,18,26,34,48]	6.5	12.66
	[0,8,16,18,32,40,48]	6.5	12.66
	[0,2,10,18,32,40,48]	6.5	12.66
	[0,8,16,24,32,40,48]	6.81	9.54
2	[0,5,4,99,81,37,71,15]	8.0	14.25
	[0,5,61,81,37,71,15]	8.39	14.22
	[0,36,4,99,81,37,71,15]	8.73	12.69
	[0,5,61,32,42,44,71,15]	9.54	11.9



(a) Scenario 1

(b) Scenario 2

Figure 6: Pareto Optimal Sets.

as diverse as possible in the obtained non-dominated set. In terms of the former goal, the set of non-dominated solutions presented were the best among all runs of the SPEA algorithm whose goal was to minimize both objectives (delay and ETX). Figure 6 shows that solutions from scenario 2 are better distributed across the POS in comparison to those of scenario 1. Despite this, both sets of solutions satisfy the latter goal.

6.3. QoS Routing

A WMSN routing protocol must take into account a set of end-to-end QoS metrics like bandwidth, delay, packet loss, etc. The QoS requirements can be met if one or multiple paths are used.

For a single path routing protocol, like DSR, whose objective is to discover paths on-demand from a source node to a destination node, hop-count is the only metric taken into account when a path is to be chosen among those discovered. Since no additional information is available to DSR, the path with the least number of nodes is selected and used to forward data. Hop-count is a simple metric because it does not require additional information to be collected and/or maintained by the nodes.

HTLC-MeDSR attempts to use multiple paths between a given source-destination pair if they exist. If the paths are carefully selected, the use of multiple path has advantages such as fail tolerance, load balancing and data aggregation. During the route selection process, HTLC-MeDSR takes into account ETX and CF among paths.

Table 6 shows average objective function values over 10 simulation runs with 95% confidence interval values. The objective function values for the proposed algorithm were averaged from the 4 non-dominated solutions obtained. It can be seen that the proposed SPEA outperforms DSR and HTLC-MeDSR in both metrics for the considered scenarios.

DSR uses only one path between the source and destination nodes in both scenarios. If a node fails to send a packet a certain number of times, it discards the packet and considers that the destination node is no longer available. Since DSR does not have any mechanism to distinguish collision losses from mobility-induced errors, a route maintenance procedure is initiated which penalizes the packets end-to-end delay, as can be seen on Table 6.

On the other hand, HTLC-MeDSR uses two independent paths to forward

Table 6: Average Objective Function Values with 95% Confidence interval

		Objective Functions		Confidence Intervals	
	Protocol	ETX	Delay (ms)	ETX	Delay
Scenario 1	DSR	N/A	313.92	N/A	0.359
	HTLC-MeDSR	12.24	52.82	0.76	0.020
	Proposed SPEA	5.56	12.04	0.12	0.001
Scenario 2	DSR	N/A	689.43	N/A	0.571
	HTLC-MeDSR	19.08	43.77	5.94	0.013
	Proposed SPEA	8.88	13.27	1.47	0.001

traffic. Differently from DSR, HTLC-MeDSR uses probe packets to identify routing failures, which reduces packet losses and consequently unnecessary route maintenance operations. As only one source rate was considered, contention and collisions are the main reason for the end-to-end delay values presented on Table 6.

Table 7 shows ETX and end-to-end Delay improvement ratios between the proposed SPEA and the routing protocols (DSR and HTLC-MeDSR) for scenario 1 and scenario 2. As can be seen, the proposed SPEA is 2.2 and 2.15 times better in terms of ETX than HTLC-MeDSR for scenarios 1 and 2 respectively. In terms of end-to-end delay, the proposed SPEA is 26.07 and 51.95 times better than DSR, and 4.39 and 3.3 times better than HTLC-MeDSR, for scenarios 1 and 2 respectively.

Table 7: Proposed SPEA improvement ratio for both scenarios

	Protocol	ETX	Delay
Scenario 1	DSR	N/A	26.07
	HTLC-MeDSR	2.2	4.39
Scenario 2	DSR	N/A	51.95
	HTLC-MeDSR	2.15	3.30

6.4. Discussion

It is important to mention that, the improvement ratios presented in the previous sections were obtained comparing simulation results of DSR and HTLC-MeDSR, with the result of an optimization algorithm (an ideal situation) for both scenarios. Even if any of the optimal solutions found by the MOEA algorithm was used, due to contentions and collisions, a regular routing protocol such as DSR would discard these optimal routes and look for new ones during the route maintenance operation.

As mentioned before, HTLC-MeDSR incorporates a set of mechanisms, such as the use of probe packets and different short retry limits at MAC layer, and the use of ETX and CF to find high throughput paths with low route coupling among them at routing layers. During route discovery, the protocol collects network information and uses it to build a graph which is later on used by a path finding algorithm, like Dijkstra's. It is assumed by the authors of [14] that the destination node is powerful enough to run this type of algorithms. Thus, the proposed MOEA could be incorporated on HTLC-MeDSR route sets building procedure to find the optimal routes from the network topology graph.

Steps 2 and 4 in our MOEA algorithm (in Section 4.3) use also a path finding algorithm, e.g., BFS. In Step 2, BFS is used to create a set of individuals that are used later to create the initial population. The path finding algorithms ensure that the created individuals are feasible, by creating them using edges that were provided by the neighborhood information that was collected during the route request process. Otherwise, if nodes were randomly selected to create the initial population, more generations would be necessary for the algorithm to converge, since many non-existing edges could have been created. Another reason is that a fully connected network is not considered in this paper.

It was mentioned that due to the BFSs time complexity, the graphs branches were probabilistically explored to reduce the time necessary to create the set of individuals. We noticed that the MOEA algorithm would converge to a local solution instead of a global one, if the population set was not composed of most of the source nodes direct neighbors. Thus, it is desirable that the algorithm that creates the set of individuals, explores branches composed by the source nodes direct neighbors, even if a probabilistic approach is used.

It was also previously stated that WMSN applications have different QoS requirements such as, bounded latency or delay, throughput, jitter, availability and energy consumption. The proposed approach uses two objective functions: delay and ETX. ETX allows finding high throughput paths taking into account the effects of link loss ratios, asymmetry in the loss ratios between the two directions of each link, and the interference among the successive links of a path. If the number of objectives were increased, what happens in this cases is the increase in the problems complexity, as the search space changes from bi-dimensional to tridimensional, increasing also the number of candidate solutions to be analyzed. But for the problem in hand, delay and ETX are the most relevant objectives. However, other pairs of objectives could have been selected which would have kept the algorithms complexity similar.

In this paper, only static simulation scenarios were considered. Nodes mobility still presents a considerable challenge for most WMSN routing protocols, since nodes get more often unreachable, rendering paths useless. A way of addressing the nodes mobility issue is to use a store, carry and forward approach more common in Delay Tolerant Networks [25]. The use of MOEA algorithms in DTNs is still an open research area.

7. Conclusions and Future Work

A multi-objective optimization algorithm aims at producing (1) solutions as close as possible to the POS, and (2) solutions as diverse as possible in the obtained non-dominated set. This diverse set of optimal solutions expresses trade-offs between different objectives. Routing protocols for WMSN must take into account a set of QoS requirements like bandwidth, delay, energy consumption. The ETX metric allows finding high throughput paths on a multi-hop wireless network, and incorporates the effects of link loss ratios, asymmetry in the loss ratios between the two directions of each link, and the interference among the successive links of a path.

In the route selection process, DSR only considers hop count, not meeting WMSN QoS requirements. Hop count does not consider the paths links conditions. HTLC-MeDSR uses ETX during the path selection process to evaluate link conditions along the path. Since HTLC-MeDSR is a multipath routing protocol, it also considers the Correlation Factor during the path selection process, to find multiple paths with minimum cross interference among a source-destination pair. The proposed MOEA algorithm allows finding paths that minimize both objectives, and paths that express trade-offs among objectives.

The paths found by the proposed SPEA present 2.2 and 2.15 times less ETX than those found and used by HTLC-MeDSR for scenarios 1 and 2 respectively. In terms of end-to-end delay, the paths found by the proposed SPEA present 26.07 and 51.95 times less delay than the ones found and used by DSR, and 4.39 and 3.30 times less delay than the ones found and used by HTLC-MeDSR, for scenarios 1 and 2 respectively.

The insertion of the proposed MOEA on HTLC-MeDSR route sets building procedure and subsequent evaluation is left for future work.

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