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A New Weighted Shortest Path Tree for Convergecast Traffic Routing in WSN

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***Abstract*—One of the widely used communication patterns in WSN is routing convergecast traffic to one or more sinks. In order to collect data at a sink, most existing systems use a tree rooted at the sink as underlying structure. We consider in this paper the Shortest Path routing Tree problem in WSN under different metrics; we show that the basic approach commonly used in the literature is unsuitable for the many-to-one WSN when considering some metrics. Indeed, existing SPT approaches aim to construct a tree rooted at the sink such that the cost of the path from any node to the sink is minimal, while the cost of a given path is computed as summation of the costs of links that compose this path. However, in many-to-one WSN, links which are close to the sink are more solicited to route packets towards the sink and, hence, they are more critical than other links. Therefore, links in the tree should not have the same weight. We propose in this paper a new weighted path cost function, and we show that our cost function is more suitable for WSN. Based on this cost function, we propose a new efficient shortest path tree construction which does not introduce any new communication overhead compared to basic SPT schemes. We consider, then, the particular case of energy-aware routing in WSN when we apply our new solution in order to construct more suitable energy-aware SPT. We conduct extensive simulations which show that our approach allows to enhance the network lifetime up to 20% compared to the basic one.**

***Index Terms*—Wireless Sensor Networks (WSN), Shortest Path Tree (SPT), weighted path cost function, energy-aware routing.**

I. Introduction

A wireless sensor network (WSN) is composed of a set of tiny autonomous nodes with sensing, computation, and wireless communication capabilities [1]. The main purpose of such networks is to collect information from a supervised environment or a target object and then send it to a base station usually called the sink. The sink is supposed to be a particular node with plentiful resources. Routing trees are typical structures widely used in WSN to deliver data to the sink, most of existing approaches propose to construct and maintain a tree rooted at the sink in order to gather all collected data at the sink, while minimizing a given cost.

The Shortest Path Tree (SPT) approach is one of the most commonly used methods to construct routing trees in the many-to-one networks and particularly in WSN [2]. The goal of SPT algorithms is to construct a tree rooted at the sink such that the path cost from any node to the sink is minimal. In existing construction algorithms, the cost of a path is computed as summation of the cost of links that compose the path while the link cost is computed depending on the routing strategy: for instance, when data is routed on minimum hop paths leading to the sink, the link cost is set to be one and the cost of a path gives the hop count to the sink. In energy-aware solutions, the used metric can be the energy dissipation through the link [3][4], the remaining energy level [5] or a combined metric [6][7]. Congestion-aware strategies [5] consider the message queue length as metric while the number of neighbors is the main metric in connectivity-aware strategies. Some existing solutions [8] [9] use the quality of link as metric to compute costs, this allows to reduce the average number of retransmissions. Other metrics have been used in the literature such us the latency in time-dependent strategies [10], physical distance and different QoS metrics.

In all SPT based solutions, the cost of a given path is computed as a uniform summation of the costs of links that compose the path; all links within a path are given the same weight. We show in this work that the basic path cost computation is unsuitable for the many-to-one WSN. Indeed, links which are closer to the sink are more critical than the other links. For example, in energy-aware strategies, first level nodes are more solicited by the routing process and are usually the first nodes which fail due to the energy exhaustion. The residual energy of the first level nodes is then more important than the energy amount of the second level ones and so on. Similarly, in congestion-aware strategies, the links which are close to sink are more solicited to route packets towards the sink and hence they are more critical than the other links.

In this paper, we propose a new weighted global cost function more suitable for many-to-one WSN. We assign efficiently decreasing weights to link costs depending on their levels in a given path. We propose, then, an efficient distributed algorithm to construct the shortest path tree through computing minimum cost values based on the defined path cost function. We apply finally our approach to energy-aware routing context and we explain how our approach allows to enhance of the network lifetime. We conduct extensive simulations and we present and discuss the results.

The contributions of our work can be summarized in the following points:

- We show that the basic SPT approach is unsuitable for the many-to-one WSN when using some metrics.
- We define a new weighted path cost function, we assign

to link costs decreasing weights depending on their levels in the path.
- We propose an efficient weighted Shortest Path Tree construction based on the defined path cost. Our construction does not introduce any new extra-communication overheads and have the same complexity as the basic one.
- We apply our approach to the energy-aware routing context where we show that it allows to enhance the network lifetime.

To the best of our knowledge, this work is the first to define a path cost function based on the summation of decreasing multiplicative factor which takes into consideration the concentric convergecast nature of WSN communications. Moreover, we design our cost function is such a way that the computation and the maintaining of the minimum cost values and so the weighted SPT can be done without any extra-communication overheads or significant computation overheads. Without loss of generality, we focus in this paper on WSN. Although, the solution that we propose can also be used in conventional networks and, in particular, many-to-one ad-hoc wireless networks.

The remainder of the paper is organized as follows. In section 2 we give an overview of the basic SPT, we focus on the tree construction and the update strategies. In section 3, we present the main related works using the SPT approach and we explain why this approach is unsuitable for the many-to-one WSN. In section 4, we present our new cost function and the weighted shortest path tree construction; we show the proposed solution is more suitable for WSN. In section 5, we apply our new approach to the energy-aware routing in WSN; we show through simulations that our solution enhances the network lifetime up to 20% thanks to the weighted path cost function. We outline, finally, some conclusions in section 6.

II. Background: Basic Shortest Path Tree Approach

In this section, we present the basic SPT approach widely used in the literature; we explain the tree construction as well as the different approaches used to maintain the constructed tree. Before that, let us present the network model that we use in the following sections.

A. Network model

Let $(v_1, v_2, ...v_n)$ be the sensor nodes and let $s = v_0$ be the sink. We assume that all nodes including the sink have the same transmission range denoted by r. We model the WSN as an graph $G = (V, E)$ where V and E represent respectively the node set and the link set. If a node v_j is within the transmission range of a node v_i ($d_{i,j} = dist(v_i, v_j) \leq r$) then the edge $e_{i,j} = (v_i, v_j) \in E$. We denote the neighborhood of a node v_i by $N(v_i)$:

$N(v_i) = \{u \in V - \{v_i\} | dist(u, v_i) \leq r\}$.

To each directed edge $e_{i,j}$, we assign a cost $C_{i,j}$ which is computed depending on a given metric. We denote by D_{v_i}, the minimum cost to reach the sink from the node v_i which is the cost of the shortest path from the node v_i to the sink. It is important to note that the cost of a path P denoted by $Cost(P)$ is computed as the summation of costs of links that compose P.

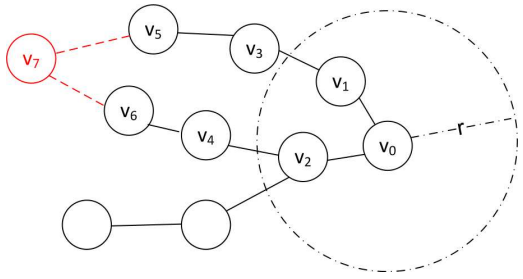


Fig. 1. Shortest Path Tree illustration

B. Basic Shortest Path Tree Construction

The aim in traditional shortest path tree approaches is to construct a tree rooted at the sink in such a way that the cost of the path to the sink is optimal for each node v_i in the tree. The cost of a path is computed as the summation of the link costs. For example, in figure 1, the cost of the path $P_1 = (v_5, v_3, v_1, v_0)$ is given by :

$Cost(P1) = C_{1,0} + C_{3,1} + C_{5,3}$

In the general case, let $P = (v_{i_n}, v_{i_{n-1}}, , v_{i_1}, v_{i_0} = v_0)$ be a path between node v_{i_n} and the sink v_0, the corresponding cost of a P is:

$$Cost(P) = \sum_{k=1}^{n} C_{i_k, i_{k-1}}$$

Many algorithms were proposed in the literature to compute the SPT. Most of them are based on distributed versions of Dijkstra's algorithm or Bellman-Ford algorithm [11]. We focus in this paper on the Bellman-Ford based algorithms knowing that our solution can be easily adapted to other algorithms. The Bellman-Ford algorithm generates the SPT by the iteration:

$D_{v_i}^{h+1} = \min_{u \in V} [C_{u,v_i} + D_u^h]$, starting from conditions:
$D_s^h = 0$ for all h , $D_{v_i}^0 = \infty$ for all $i \neq 0$

Where $D_{v_i}^h$ is the D_{v_i} value at the iteration h. The algorithm of Bellman-Ford terminates after at most ($h \leq n$) iterations. The Bellman equation, obtained by the termination of the Bellman-Ford algorithm, is given by:

$D_s = 0$
$D_{v_i} = \min_{u \in V} [C_{u,v_i} + D_u]$

This equation allows to construct the SPT. Indeed, the last node which allows to enhance the cost value is the parent in the shortest path tree. Bertsekas and Gallager, gives in [11], a distributed asynchronous version of the Bellman-Ford algorithm. They show that we can settle for the neighborhood of a node v_i given by the transmission range for example. The new distributed version was given by the iteration:

$D_{v_i}^{h+1} = \min_{u \in N(v_i)} [C_{u,v_i} + D_u^h]$, starting from conditions:
$D_s^h = 0$ for all h, $D_{v_i}^0 = \infty$ for all $i \neq 0$

Where $N(v_i)$ is the neighborhood of the node v_i. Bertsekas and Gallagher [11] proved that convergence occurs even if different nodes are slow to propagate or calculate their D_{v_i} and/or $C_{i,j}$.

C. Shortest Path Tree Update

In WSN, the link costs are usually not static and may change. For example, in energy-aware context, the remaining energy of nodes decreases continuously. In addition, the physical topology may change because of node mobility or failure and/or new node deployment. Similarly, in the congestion-aware, the link congestion costs change constantly. In order to maintain the optimal SPT structure, we identify two approaches in literature:

1) The periodic tree re-construction: In this approach, the sink initiates the setup phase periodically in order to reconstruct a new tree structure. The choice of the period may impact the network performance. Indeed, if the period is too small, then the network may be congested. If the period is too large, then the constructed structure may not be up-to-date for a long time.

2) The adaptive update: In adaptive approaches, the constructed tree is automatically updated during the routing process and no maintenance phase is required. Usually, these solutions propose to add a field containing the minimum cost value to the data packets. Thanks to this field, each node may update its parent and its minimum cost when hearing its neighbor packets. The adaptive update strategies do not guarantee the SPT at any given time; however, it ensures an approximated SPT. If link costs become stable the structure converges to the SPT. These strategies are more suitable for highly dynamic WSN because the periodic tree re-construction may be costly.

III. Related Works

Routing in wireless sensor networks has been extensively investigated the last decade, a lot of solutions were proposed in this field. We focus in what follows on shortest path based routing strategies, comprehensive surveys on routing for WSN can be found in [12] [13] and [14].

Many research works have used explicitly or implicitly the SPT construction in WSN. Depending on the routing strategy, these works propose an adequate link cost definition. In the basic approaches, the aim was to minimize the hop count towards the sink [15][16]. The link cost is set to be one and the path cost, which is computed as the summation of link costs, gives the hop count from the source node to the sink. Since the energy consumption and the end-to-end delay are correlated to the path length, the use of shortest paths in terms of hop count reduces the energy dissipation and the end-to-end delay.

In energy-aware solutions, many metrics were used in the literature. When the energy dissipation through the link is used as metric [3][4], the total consumed energy to reach the sink is minimized. This approach is called Short Path-power routing [6] or Minimum Total Energy (MTE) routing [7].

TABLE I
SUMMARIZE OF USED METRICS IN TREE BASED ROUTING PROTOCOLS

Metric	Main objectives
hop count	minimize the length of used paths reduce the energy consumption reduce the end-to-end delay
energy dissipation	minimize the global energy consumption
remaining energy	enhance the first node failure time
link quality	reduce the retransmission number
latency	minimize the end-to-end delay
number of neighbors	enhance the network connectivity
message queue length	reduce the congestion

In [6], authors present a *SP-power routing* algorithm based on the energy dissipation through the link as metric, they propose also a *SP-cost routing* where the cost function was proportional to the inverse of the remaining battery power. They present finally a *SP-power-cost routing*, in order to optimize a combination of the energy dissipation and the remaining energy level. Route constructions were based on the Dijkstra algorithm. When using the *SP-power routing*strategy in static WSN, all the traffic is routed on the same minimum energy paths even the tree update is periodic or adaptive, nodes of theses paths exhaust quickly their energy. However, when we base on the remaining energy as metric, the paths to the sink may change and the time to the first node failure is enhanced.

Authors in [7] proposed a link metric which combines the transmission energy amount, the reception energy amount, the initial energy level and the remaining energy level of both the source node and the destination one. Authors proposed to use the distributed Bellman-Ford algorithm in order to construct the SPT based on the defined metric. In [17], authors propose an energy dissipation prediction model to compute the link metrics. They propose to use the principle of Prim and Dijkstra to build the SPT to prolong network lifetime while using clustering.

In [5], authors propose an adaptive routing tree protocol for WSN where the setup phase is based on the shortest path tree construction with a learning-based adaptive update. Authors propose two strategies: *the energy-aware* one where they use the remaining energy level of the source node to compute the link cost and the *congestion aware strategy* where they compute the link costs depending on the current transmission queue length of the source node.

Authors in [18] proposed to use the outward and inward link quality as metric. Based on this metric, a distributed algorithm is used to construct a SPT. Liang et al. [19] use as metric the expected transmission count (ETX) which is estimated based on link quality indicators. Link quality metrics were also used to construct routing trees in [8], [9] and [20]. Other cost metrics were used in the literature such as the latency in time-dependent strategies [10], the number of neighbors in connectivity-aware strategies, the physical distance and different QoS parameters.

Discussion:

We summarize in table I the main metrics used in the literature to construct routing trees. We notice that research works to date has tended to focus on the link metrics in the aim to enhance some network performances. However, a little attention has been paid to the path cost computation. Indeed, as shown above, all the surveyed solutions using shortest path constructions compute the cost of a given path as a uniform summation of costs of all links that it contains; all links in a path are given the same weight. In fact, this basic approach is unsuitable for routing convergecast traffic in the many-to-one WSN when considering some metrics. Indeed, links which are closer to the sink are more critical than the others.

By the way of illustration, let us consider the remaining energy of the source node as metric to compute the link costs, it is obvious that the remaining energy of the first level nodes is more important than the other node's energy level because the sink neighbors are more solicited by the routing process, so they exhaust their energy much sooner than the other nodes. In figure 1, let us assume that the node v_7 have to choose between the two paths $P_1 = (v_7, v_5, v_3, v_1, v_0)$, $P_2 = (v_7, v_6, v_4, v_2, v_0)$, in such a way to minimize the global cost to the sink. If we suppose that the cost of a path is a uniform summation of the path link costs, the node v_7 may select the path node P_1 because the energy level of the nodes v_7 and v_3 is very high. However, the energy level of the node v_1 may be very low. Based on a uniform cost function, many nodes may choose paths containing the node v_1 and the latter exhausts its energy much sooner than the other sink neighbors. In the same way, we can show that basic SPT approach is unsuitable for congestion-aware routing in WSN and for some QoS-aware strategies. Indeed, with a uniform random deployment, the number of nodes at the first level is lower than the number of nodes at the second level and so on, the first level links are more solicited than other links and their congestion is more probable than other links.

In contrast to the basic approaches, we propose in this paper a new weighted global cost function more suitable for many-to-one WSN. In the next section, we explain the new weighted path cost function and we propose a distributed algorithm which allows to construct efficiently the corresponding weighted SPT.

IV. Our Solution: A new weighted shortest path tree construction

In contrast to the basic SPT construction approach, we aim in our solution to privilege links which are closer to the sink since they are more critical. In order to achieve this aim, we design a new weighted global cost function which considers the costs of the first level links more than the second level ones, the costs of the second level links more than the third level ones and so on. Our design was driven by the following goals:

- **Weighting the global cost function**: In order to privilege the costs of links which are closer to the sink, links may be assigned decreasing weights depending on their level in a given path.
- **Simplicity**: Because of the resource constrained environment of WSN, the computation of the cost values and the construction of the new SPT may be done efficiently without new extra control message or significant computational overheads.
- **Scalability**: The proposed solution may be scalable and efficient for large scale WSN where the number of nodes is high.
- **Generic solution**: The proposed solution may be applicable to different routing strategies including energy-aware, congestion-aware, connectivity-aware and QoS aware routing strategies.

A. A new weighted global cost function

In order to privilege the costs of links depending on their levels in a path, we define the new path cost as a weighted summation of costs of all links that the path contains. Let us $P = (v_{i_n}, v_{i_{n-1}}, , v_{i_1}, v_{i_0} = s)$ be a path which consists of n links. We define the new cost of P, that we denote in the following by α-Cost, as follows :

$$\alpha\text{-Cost}(P) = \sum_{k=1}^{k=n} \alpha^{n-k} C_{i_k, i_{k-1}}$$

Where α is a parameter of our protocol ($\alpha \geq 1$), raised to the corresponding power, it determines the weight attributed to the link cost in order to compute a path cost. As we will show, we chose decreasing power of a parameter α to simplify the computation and the update of the minimum cost values. We discuss later in this paper the choice of the parameter α depending on the routing strategies. Using this new cost function, the cost of the path $P_1 = (v_7, v_5, v_3, v_1, v_0 = s)$ given in figure 1, becomes:

$\alpha\text{-Cost}(P_1) = \alpha^3 C_{1,0} + \alpha^2 C_{3,1} + \alpha C_{5,3} + C_{7,5}$

While the cost of the path $P_2 = (v_7, v_6, v_6, v_2, v_0 = s)$ becomes:

$\alpha\text{-Cost}(P_2) = \alpha^3 C_{2,0} + \alpha^2 C_{4,2} + \alpha C_{6,4} + C_{7,6}$

If we consider the energy-aware context where link costs depend on the remaining energy of nodes, the choice of the shortest path to the sink by the node v_7 using our path cost function is more suitable than the basic approach. Indeed, when computing the cost of P_1, the remaining energy level of v_1 is implicitly considered more than the remaining energy level of node v_3, more than the remaining energy level of node v_5 and so on. Similarly, when computing the cost of P_2, the remaining energy level of v_2 is considered more than the energy level of v_4 and so on. This cost function is then more suitable for many-to-one WSN when using the energy-aware strategy since the criticality of links within a given path depends on their levels. The same cost function is also suitable when using congestion-aware strategies in WSN where the message queue length is used as link cost metric. The sink neighbors are more solicited by the routing process than the

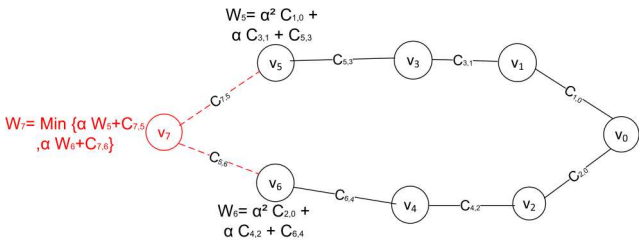


Fig. 2. Illustration of the weighted cost path computation

second level nodes and so on. So, the criticality of links within a path depends also on their levels.

In what follows, we give a distributed algorithm to compute the new shortest path tree depending on the defined cost function. In addition to the network model presented in section 2, we define W_{v_i} as the minimum α-Cost to reach the sink from a given node v_i. We define also the α-shortest path tree as the tree rooted at the sink in which the α-Cost of the path to the sink is optimal for each node v_i.

B. An Efficient α-Shortest Path Tree Construction

Most of existing distributed algorithms computing shortest path routing trees can be adapted in order to compute the novel α-shortest path tree relying on the new proposed cost function. Indeed, the α-Cost of a $n+1$ hop path ending at the sink is computed as the last link cost plus α multiplied by the n hop sub-path (see figure 2).
Similarly to the distributed asynchronous Bellman-Ford algorithm, the construction of the α-SPT can be given by the iteration:

$$W_{v_i}^{h+1} = \min_{u \in N(v_i)} [C_{u,v_i} + \alpha \times W_u^h]$$

Starting from conditions:

$$W_s^h = 0 \text{ for all } h,\ W_{v_i}^0 = \infty \text{ for all } i \neq 0.$$

Where $N(v_i)$ is the neighborhood of the node v_i. Similarly to proofs given in [11], we can prove that this algorithm converges to the α-shortest path tree even if different nodes are slow to propagate or calculate their W_{v_i}, and/or $C_{i,j}$.

We give in algorithm (1) a distributed construction of the α-SPT. The sink initiates the construction by sending a broadcast message with its null cost. When a node receives the setup message, it computes the α-cost to the sink if it selects the sender as parent, for that, it multiply the received cost by α and add the link cost. If the computed value is lower than the local minimum cost, the node updates its cost, selects the sender node as temporary parent and re-broadcasts the setup message with the new local cost.

We notice that our construction has the same complexity as the basic shortest path tree construction without any extra-communication overheads. In addition, the additional computation overhead is insignificant. Our solution can be used with periodic update as well as the adaptive approaches.

Input: Network topology G
Output: α-Shortest Path routing Tree
Initialization:
$W_s = 0, par(s) = s$
$W_{v_i} = \infty$, $par(v_i) = Null$ for $i = 1, ..., N$
$Sink\ s$: Broadcast $\langle s, W_s \rangle$
Upon receiving $\langle v_j, W_j \rangle$ **at** v_i
if $(W_{v_i} > \alpha \times W_{v_j} + C_{i,j}\ )$ **then**
    $W_{v_i} = \alpha \times W_{v_j} + C_{i,j}$;
    $par(v_i) = v_j$;
    Broadcast $\langle v_i, W_i \rangle$;
end

Algorithm 1: α-shortest path tree construction algorithm

All existing strategies described above can be adapted to maintain the constructed α-SPT.

In the next section, we apply the α-shortest path tree to the energy-aware routing and we show through simulations that our approach allows to enhance the network lifetime compared to the basic one.

V. Application to the Energy-Aware Context

The routing in wireless sensor networks has been extensively investigated [12] [14][13] in the literature so far, a particular attention was paid to energy-aware routing. As shown before, the shortest path tree construction based on the remaining energy is one of the favorite approaches commonly used to ensure energy-aware data routing in WSN. In this section, we apply our solution to the energy-aware context when we consider a cost function based on the residual energy level of nodes. First, we model the energy consumption and we define the network lifetime of any constructed routing tree. Next, we compare our approach with different α values to the basic shortest path tree one and we present and discuss the simulation results.

A. Energy model and network lifetime definition

In what follows, we use the model defined in section 2. In addition, we assume that each node v_i has a battery with a finite initial energy level E_i while the sink is supposed to have unlimited energy amount. We rely on the well known model proposed in [21] which was widely used in the literature. To send one bit of data from node v_i to node v_j, the consumed energy at the node v_i is given by:

$$TX^{i,j} = E_{elec} + E_{amp} \times d_{i,j}^2$$

While the consumed energy, when receiving one bit of data from any node at the node v_i, is given by:

$$RX^i = E_{elec}$$

Where E_{elec} is the energy consumed in the transceiver circuitry when transmitting or reciving, and E_{amp} is the energy consumed at the transmit amplifier to achieve one meter. Without loss of generality, we assume that we use a TDMA-like MAC which allows to avoid collisions. On the other hand, we focus on the power consumption during the transmission and the reception and we neglect the energy consumption

during the idle mode.
We assume that each node generates periodically one data packet of k bits, we denote a period time by $round$. We define $\pi^{i,j}$ as the amount of data sent from node v_i to node v_j at each round. For any given tree structure, we define:

- $Child_i$: the direct children of node v_i in the tree;
- p_i the unique parent of the node v_i in the tree.

We define the network lifetime as the time until the first node runs out of energy. A detailed discussion of many network lifetime definitions used in the literature can be found in [22]. Using our model, the network lifetime of a given tree is then defined as:

$$\begin{aligned} &LifeTime(Tree) = Max\ T \\ &s.t.\ \ \forall v_i \in V : \\ &T \times RX^i \times (\sum_{j \in Child_i} \pi^{j,i}) + T \times TX^{i,p_i} \times \pi^{i,p_i} \leq E_i, \\ &\pi^{i,p_i} = \sum_{j \in Child_i} \pi^{j,i} + k \end{aligned} \quad (1)$$

The lifetime of each node is then:

$$T_i = \left\lfloor \frac{E_i}{RX^i \times (\sum_{j \in Child_i} \pi^{j,i}) + TX^{i,p_i} \times \pi^{i,p_i}} \right\rfloor \quad (2)$$

The system 1 can then be written as follows:

$$\begin{aligned} &LifeTime(Tree) = Min_{v_i \in V} T_i \\ &s.t.\ \ \forall v_i \in V : \\ &T_i = \left\lfloor \frac{E_i}{RX^i \times (\sum_{j \in Child_i} \pi^{j,i}) + TX^{i,p_i} \times \pi^{i,p_i}} \right\rfloor \\ &\pi^{i,p_i} = \sum_{j \in Child_i} \pi^{j,i} + k \end{aligned} \quad (3)$$

We use this definition to compare the network lifetime of our approach when ($\alpha > 1$) to the network lifetime of the basic SPT.

B. Simulation Results

Based on the presented energy model, we conducted extensive simulations using MATLAB in order to compare the network lifetime depending on α values while considering the impact of the network density, the network size and the network topology. We recall that the case $\alpha = 1$ represents the basic SPT.
We suppose that each node has an initial energy randomly selected between 5 joules and 20 joules. We summarize in table II the other common simulation parameters.
To each link $e_{ij} = (v_i, v_j)$, we assign the following cost:

$$C_{ij} = e^{\frac{E_{max} - E_i}{\beta}} \quad (4)$$

Where: E_{max} represents the maximum energy level and β is used in order to obtain costs in a reasonable scale, its value does not influent critically the constructed structure. The defined link cost function allows, then, to obtain a value

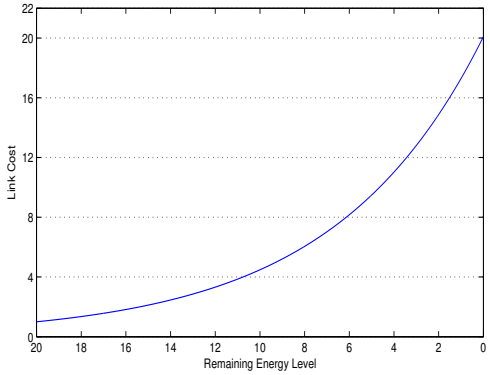


Fig. 3. Link cost depending on the remaining energy

TABLE II
SUMMARIZE OF THE COMMON SIMULATION PARAMETERS

Parameter	Value
E_{elec}	50 $njoules$
E_{amp}	100 $pjoules/m^2$
Transmission range (r)	50 $meters$
Generated data size per round (k)	16 $bytes$
E_i (min)	5 $joules$
E_i (max)	20 $joules$

increasing from 1 to $e^{\frac{E_{max}}{\beta}}$, when the energy level of the source node decreases from E_{max} to 0. In simulations, we chose $\beta = \frac{E_{max}}{3}$ in order to obtain link costs belonging to the interval $[1, e^3]$. We plot in figure 3 the link cost variation when the remaining energy decreases from $E_{max} = 20$ joules to 0 joules.

1) Impact of network density: In this first scenario, we studied the impact of network density on the network lifetime of the constructed α-shortest path tree. The deployment field is supposed to be a circle with a radius $R = 200\ meters$, the sink node is set to be at the centre and all sensor nodes are scattered in the field in a random way.
We plot in the figure 4, the network lifetime depending on

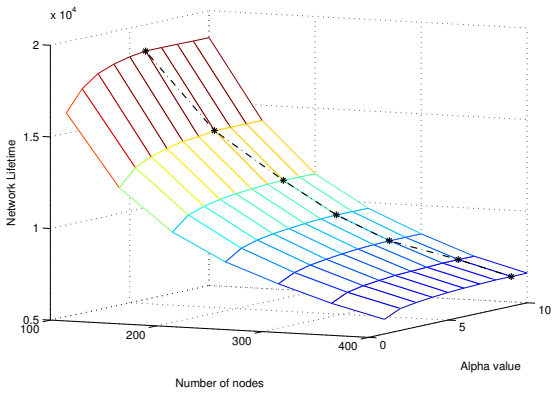


Fig. 4. Netw. lifetime depending on the α values and the netw. density

the α value, when the number of nodes is between 100 and

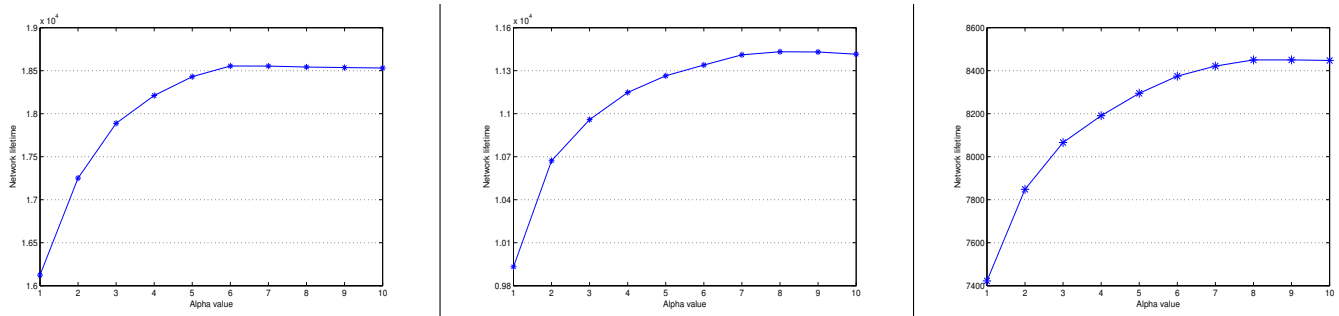


Fig. 5. Network lifetime depending on the α values

400. All the reported results are averaged over 750 runs. In figure 5, we consider the particular cases when the number of sensor nodes is respectively 100, 200 and 300.

Results show that higher is α better is the network lifetime, we choose the optimal α value as the value after which the network lifetime reaches the maximum value. As shown in figure 5, the optimal value of α is 6,8 and 8 when the number of nodes is 100, 200 and 300 respectively.

In figure 6, we plot the network lifetime depending on the number of nodes (network density) when α=1 (basic approach), 4 and 7 respectively. The figure shows that our solution enhances the network lifetime up to 17% compared to the basic approach. Indeed, in 99% of cases, the first node which fails is a sink neighbor; our approach based on the weighted path cost function allows to privilege the node remaining energy depending on their hop proximity to the sink. Thus, we choose paths having higher remaining energy at the most critical nodes.

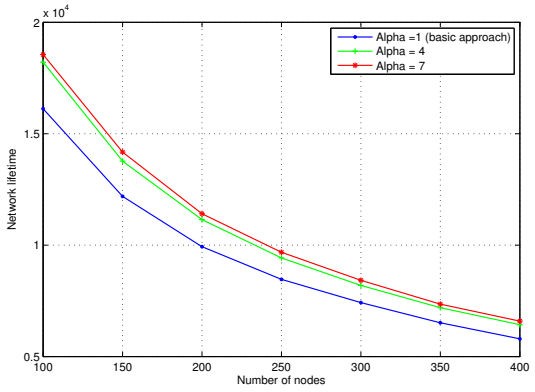


Fig. 6. Netw. lifetime depending on the netw. density with different α values

2) Impact of network size: In this second scenario, the network density is constant and set to be 20 nodes per πr^2 $m \times m$. Hence, we varied the radius of the deployment area R depending on the number of sensor nodes, the sink node is always set to be at the centre. We study then the impact of the network size on the network lifetime with different α values. All the reported results are averaged over 750 runs.

In figure 7, we plot the network lifetime when the network

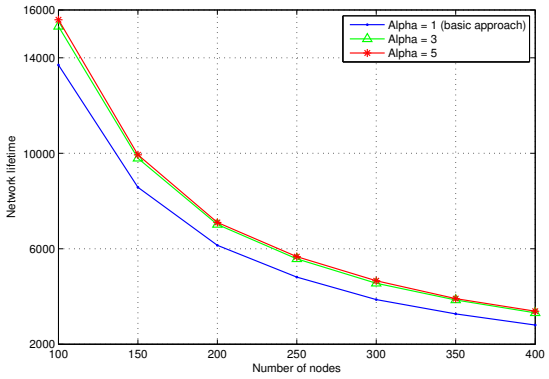


Fig. 7. Netw. lifetime depending on the netw. size with different α values

size is between 100 and 400 nodes and when α is respectively 1, 3 and 5. The figure shows that the use of the weighted shortest path tree allows to enhance network lifetime up to 15% compared to the basic approach. Otherwise, the obtained results showed that the best network lifetime is reached when α is between 5 and 6.

3) Impact of network topology: In the two first scenarios, we used a uniform random distribution to model the node deployment. In order to study the impact of the network topology, we consider in this scenario another topology based on the scale free distribution widely used to model many kind of computer networks and social networks. The scale free distribution was used to model cluster-based WSN where particular nodes having more capabilities are used as routers to relay and/or to perform data fusion or aggregations [23]. In order to construct the scale-free graphs, we used the Albert and Barabasi model [24] where the network grows incrementally. The number of edges added at each step is set to be 4. We varied the α values and we calculate the defined lifetime of each constructed α-SPT. All the reported results are averaged over 750 runs.

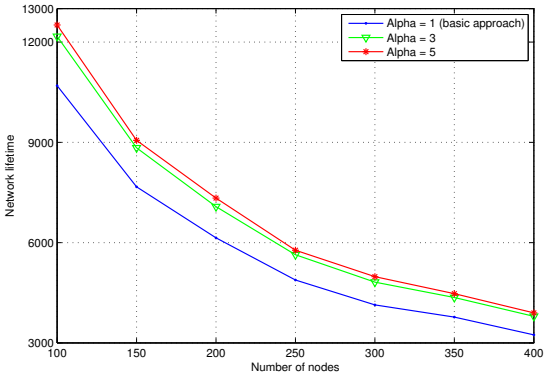


Fig. 8. Netw. lifetime depending on the number of nodes with different α values (scale free deployment)

We plot in figure 8 the network lifetime when the number of nodes is between 100 and 400 and when α is respectively 1, 3 and 5. Compared to the basic SPT construction ($\alpha = 1$) the use of the weighted shortest path tree construction with ($\alpha \geq 5$) allows to enhance network lifetime up to 20%. The best network lifetime is reached when α is between 5 and 6. We notice then that our approach (α-SPT) adapts automatically to the new free scale topology and maintains the advantage over the basic approach (SPT).

VI. Conclusion

We considered in this paper the shortest path routing tree approach which is one of the most commonly used methods to construct routing trees in the many-to-one networks and particularly in WSN. We showed that the conventional construction used in the literature is unsuitable for WSN because of the concentric nature of communications. Indeed, existing constructions aim to minimize the cost to reach the sink at each node while path costs are computed as a uniform summation of its link costs. However, in WSN, the criticality of links depends on their hop proximity to the sink. We proposed a new weighted path cost function in which we assign efficiently decreasing weights to link costs depending on their levels in a given path. Relying on this cost function, we proposed a new weighted SPT construction which does not introduce extra-communication overheads. Finally, we considered the energy-aware routing when we applied our solution to construct more appropriate routing tree. We conducted extensive simulations which showed that our approach enhances the network lifetime up to 20% compared to the basic one.

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