Fuzzy Algorithms for Maximum Lifetime Routing in Wireless Sensor Networks[1]

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***Abstract*—We address the maximum lifetime routing problem in wireless sensor networks (WSNs) and propose two online routing algorithms based on fuzzy logic, namely fuzzy maximum lifetime algorithm and fuzzy multiobjective algorithm. The former attempts to maximize the WSN lifetime objective, whereas the latter strives to simultaneously optimize the lifetime as well as the energy consumption objectives. The distinguishing aspect of this work is the novel use of fuzzy membership functions and rules in the design of cost functions for the routing objectives considered in this work. A range of simulation results obtained under various network scenarios show that the proposed approach is superior to a number of other well-known online routing heuristics, both in terms of the obtained network lifetime as well as the average energy consumption.**

I. Introduction

Wireless sensor networks (WSNs) are usually comprised of battery-operated sensor devices capable of communication and processing [1]. In the recent past, WSNs have found a number of potential applications in various fields [1], [7]. In many real life applications, battery powered wireless sensors are deployed in remote or hostile environments with a high node density. In such scenarios, power is a precious resource and there is a great need for energy efficient techniques and protocols at all the layers of WSN [7], [15].

In this paper, we address the problem at the routing layer of WSN and present two efficient routing algorithms, namely fuzzy maximum lifetime (FML) routing algorithm and fuzzy multi-objective (FMO) routing algorithm. The former attempts to maximize the network lifetime objective whereas the latter strives to simultaneously optimize the lifetime as well as the energy consumption objectives. It is worth mentioning that although minimum energy consumption is the second objective considered in the proposed FMO algorithm, the multi-objective routing framework based on fuzzy logic presented in this paper can be easily extended to incorporate other typical routing objectives such as end-to-end delay and network capacity.

The proposed techniques are based on a novel use of fuzzy functions and operators for devising weighting cost functions that are employed in solving the two above stated routing problems in WSN. The motivation for resorting to fuzzy logic in designing the objective cost functions is that fuzzy sets and membership functions have proved to be an effective mean of expressing the costs of the various objectives involved in an optimization problem [19]. As will be clear in the following sections, a fuzzy membership function provides a flexible way of translating the cost value of a given objective into a fuzzy membership value. Secondly, in case of the multiobjective routing, there is a need for designing a multiobjective aggregation function, and fuzzy logic offers a better alternative, namely ordered weighted operator (OWA) to the other traditional aggregation approaches such as weighted sum [18].

The proposed algorithms are online: an online routing algorithm finds the *best path* for each routing request without the knowledge of any future routing requests [14], [9], [10]. A routing request is initiated by a source node at any instance during the network lifetime to indicate its intention to send data packet(s) to one of the sink nodes. Further, we make no assumptions about data rates and traffic amounts. On the other hand, an offline routing algorithm requires full knowledge of all the future routing requests. Moreover, a number of existing offline routing algorithms assume that only a prefixed node (or a subset of nodes) in the entire network may act as source node(s), and that their data generation rates and traffic amounts are known *a priori*. An offline routing model may suit certain WSN applications and numerous analytical and heuristic-based offline routing approaches are found in the literature. We believe there are numerous WSN scenarios, where an online routing model may capture the event-driven WSN nature more realistically: an event may occur anywhere at any point in time, and any node that detects that event may start acting as a source node.

We conduct a performance comparison of the proposed routing algorithm to an existing well-known online routing scheme, namely Online Maximum Lifetime (OML) routing heuristic [14]. OML was shown to outperform a number of other existing maximum lifetime routing algorithms including CMAX [9], MPRC [13] and $z.P_{min}$ [3]. A range of experimental results obtained under various network scenarios indicate that the proposed FML algorithm outperforms the OML heuristic both in terms of the network lifetime as well as the average energy consumption. It should be noted that the FML algorithm has a complexity advantage over the OML algorithm since for each routing request, FML requires only one shortest path search whereas OML requires two searches.

The rest of the paper is organized as follows: In the following, we present a brief introduction to fuzzy functions and operators. Section II describes our system model and problem formulation followed by Section III that presents details of the proposed fuzzy routing algorithms. Experimental results and discussions are given in Section IV followed by references to related work (Section V) and some concluding remarks (Section VI).

A. Fuzzy Logic: An Introduction

Fuzzy Logic is a mathematical discipline invented to express human reasoning in rigorous mathematical notation. Unlike

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classical reasoning in which, a proposition is either true or false, fuzzy logic establishes approximate truth value of a proposition based on linguistic variables and inference rules. A *linguistic variable* is a variable whose values are words or sentences in natural or artificial language [19]. By using hedges like 'more', 'many', 'few', and connectors like 'AND', 'OR', 'NOT' with linguistic variables, an expert can form *rules*, which will govern the approximate reasoning.

1) Fuzzy Membership Functions:
In the context of crisp sets, a certain element is either a member or a nonmember of a set (in other words, membership is either 1 or 0), whereas in fuzzy logic, a certain element may have partial membership in a set (membership is in the range [0,1]).

A fuzzy membership function is used to compute the membership corresponding to a given value of a linguistic variable. The membership function can be designed in a flexible way in order to reflect the desired *goodness* behavior of an objective corresponding to a given value of the variable. For instance, as we shall see in Section III, we design a fuzzy membership function for computing *lifetime membership* μ_{lt} corresponding to the residual energy value of a node, where a higher value of μ_{lt} means a higher *goodness* level of the 'lifetime' objective.

2) Fuzzy Ordered Weighted Averaging (OWA) Operator:
As in the case of the proposed fuzzy multiobjective (FMO) routing algorithm, there are multiple optimization goals that we want to optimize simultaneously, we need to formulate a multiobjective cost aggregation function that may reflect the effect of all the objectives collectively as a scalar value. A common approach is to use a weighted sum based cost function. Generally, this type of cost function is not sufficient to reach the desired solution due to certain reasons [18]: the formulation of multiobjective cost functions do not desire pure "anding" or "oring" kind of aggregation operation. Fuzzy logic offers a fuzzy aggregation operator, namely the Ordered Weighted Averaging (OWA) [18], as an alternative to weighted sum, for designing a multiobjective cost function. This operator allows easy adjustment of the degree of "anding" and "oring" embedded in the aggregation. "Or-like" and "And-like" OWA operators for two fuzzy sets A and B are implemented as given in Equations (1) and (2), respectively.

$$\mu_{A\cup B}(x) = \beta \times \max(\mu_A, \mu_B) + (1-\beta) \times \frac{1}{2}(\mu_A + \mu_B) \quad (1)$$

$$\mu_{A\cap B}(x) = \beta \times \min(\mu_A, \mu_B) + (1-\beta) \times \frac{1}{2}(\mu_A + \mu_B) \quad (2)$$

where μ_A and μ_B denote the fuzzy memberships in fuzzy sets A and B respectively, whereas β is a parameter in the range $[0, 1]$ that controls the degree to which OWA operator resembles a pure "or" or a pure "and", respectively.

II. System Model and Problem Formulation

In this section, we present a brief description of our WSN system model and also formulate the maximum lifetime routing problem. We consider a static WSN deployment and model it as a directed graph $G(V, E)$ where V is the set of nodes and E is the set of edges. All the nodes have equal initial energy σ. The node batteries are neither replaceable nor remotely rechargeable. Each node $v_i \in V$ has a set of neighbor nodes (denoted as neighborhood set N_i) that v_i can each by a single hop transmission using a certain maximum transmission radius r_t. An edge $e(v_i, v_j)$ between two nodes is defined to exist only if v_i and v_j are within each others radio transmission range, i.e., if $d_{ij} \leq r_t$ where d_{ij} is the Euclidian distance between the two nodes.

The energy consumption model used in our experiments is based on the *first order radio* propagation model. According to this model the energy expended by a sensor node during transmission and reception of a k-bit packet is given by Equations (3) and (4), respectively.

$$TX_{ij} \;=\; (A + B \cdot d_{ij}^m) \cdot k \quad (3)$$

$$RX_{ij} \;=\; A \cdot k \quad (4)$$

where 'A' is distance-independent and accounts for the energy consumed in running transmitter or receiver circuitry, 'B' denotes the energy required by the transmitter's amplifier, whereas 'm' is a field constant typically in the range [2,4] and depends on certain characteristics of the wireless medium.

We assume a point-to-point communication model for our WSN scenarios where we have a set of source nodes performing sensing task as well as a set of sink nodes (base stations) that receive data from source nodes. At any time, a source node s_i may initiate a routing request $r_h(s_m, t_n)$, $h = \{1, 2, \cdots\}$, for sending its sensed data to a sink node t_n. A routing request does not imply a single data message (packet), rather it represents a sequence of data packets to be sent from the source node to a sink node. We assume there are numerous routing requests $\{r_1, r_2, r_3, \ldots\}$ during the lifetime of WSN. The goal of the proposed online routing algorithms is to efficiently route each routing request r_h, without knowledge of future routing requests r_q (where $q > h$), in such a manner that maximizes the number of successful routing requests before the end of WSN lifetime.

We employ a simple, but commonly used, WSN lifetime definition [4], [11], [17], [6]: The WSN lifetime is equal to the minimum node lifetime among all nodes in the network, i.e., the network lifetime ends as soon as any node in WSN runs out of its battery. If the lifetime of a WSN node is denoted by T_{v_i}, the WSN lifetime may be expressed as given by Equation (5).

$$T \;=\; \min_i \; \{T_{v_i}\} \qquad \forall \; v_i \in V \quad (5)$$

III. The Proposed Routing Algorithms

In the following sections, we describe the details for the two proposed routing algorithms: fuzzy maximum lifetime (FML) routing algorithm and fuzzy multiobjective (FMO) routing algorithm.

A. Fuzzy Maximum Lifetime Routing Algorithm (FML)

In order to apply fuzzy logic to the maximum lifetime routing problem, a linguistic variable *residual energy* of a node v_i, and a fuzzy set *high lifetime* are defined. A fuzzy membership function (depicted in Figure (1)) is designed to map a value of the above mentioned variable to its corresponding fuzzy lifetime membership μ_{lt}^{ij} that is assigned to each outgoing edge $e(v_i, v_j)$. As may be observed, the function assigns a high membership to an edge having a large amount of residual energy (re) at its starting node v_i. Initially, when the residual energy of a node is equal to σ, each of its outgoing edge is assigned a membership of 1.0. As the node residual energy decays, the corresponding membership falls initially at a low rate. Eventually, when the residual energy level crosses a threshold point $\alpha \cdot \sigma$ (where $\alpha \in [0,1]$ is an algorithmic parameter), the corresponding membership starts decreasing at a sharper rate. This behavior of the membership function strongly discourages the inclusion, on the selected routing path, of those intermediate nodes that have depleted their energy beyond a certain threshold value. The threshold point may be altered by adjusting the value of α. An expression for the fuzzy lifetime membership function can be derived using the equation of a line and is given by Equation (6).

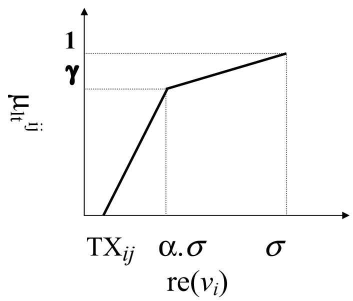


Fig. 1. A representation of fuzzy membership function for lifetime.

$$\mu_{lt}^{ij} = \begin{cases} 1-(\frac{1-\gamma}{1-\alpha})\cdot(1-\frac{re(v_i)}{\sigma}): \\ \quad if \;\; \alpha\cdot\sigma < re(v_i) \le \sigma \\ \\ \frac{\gamma}{\alpha\cdot\sigma - TX_{ij}} \times (re(v_i) - TX_{ij}): \\ \quad if \;\; TX_{ij} < re(v_i) \le \alpha\cdot\sigma \\ \\ 0: \quad if \;\; re(v_i) \le TX_{ij} \end{cases} \tag{6}$$

Here

$$re(v_i) = ce(v_i) - TX_{ij} \tag{7}$$

where $re(v_i)$ and $ce(v_i)$ denote residual energy and current energy of node v_i respectively, and $\alpha \in [0,1]$, $\gamma \in [0,1]$ are algorithmic parameters. Then a weight is assigned to each edge $e(v_i, v_j)$ using the following equation:

$$w_{ij} = 1 - \mu_{lt}^{ij} \tag{8}$$

***G* (*V*, *E*)** is the given directed graph
For each routing request ***r**$_h$* **(*s*$_m$, *t*$_n$)**
  For each edge ***e* (*v*$_i$, *v*$_j$)** in ***V***
    Compute fuzzy lifetime membership $\boldsymbol{\mu_{lt}^{ij}}$
    Assign weight $\boldsymbol{w_{ij} = 1 - \mu_{lt}^{ij}}$
  End For
  Find minimum weight path $\boldsymbol{p_h}$ from $\boldsymbol{s_m}$ to $\boldsymbol{t_n}$
  Send data along path $\boldsymbol{p_h}$
  Compute the minimum node energy in ***G* (*V*, *E*)**
  IF a node has run out of energy, stop.
End For

Fig. 2. A description of the proposed fuzzy maximum lifetime (FML) routing algorithm.

The proposed fuzzy routing algorithm (Figure 2) finds the maximum life time path as follows: When a routing request $r_h(s_m, t_n)$ is initiated, a fuzzy lifetime membership is computed for each edge using Equation (6), and hence a weight is assigned to each edge in WSN using Equation (8). Following the weight assignment, the maximum lifetime path p_h between s_m and t_n is found using Dijkstra's shortest path algorithm [8].

B. Fuzzy Multiobjective Routing Algorithm (FMO)

Most earlier routing schemes for WSNs were targeted at finding minimum energy routes; it is, therefore, interesting to investigate the impact of incorporating the minimum energy consumption as a second objective in our routing problem. We describe our fuzzy multiobjective (FMO) routing algorithm that simultaneously optimizes two routing objectives.

In order to incorporate the minimum energy consumption objective in our routing algorithm, another linguistic variable *required energy* along an edge $e(v_i, v_j)$, and a corresponding fuzzy set *low energy consumption* are defined. A fuzzy membership function (Figure (3)) is proposed to map a value of the variable *required energy* to its corresponding fuzzy minimum energy membership μ_{me}^{ij}. As may be seen, the function assigns the lowest (highest) membership value to an edge requiring the maximum (minimum) transmission energy among all the neighboring edges. This behavior of membership function encourages the selection of such edges that require lesser transmission energy. The lowest membership may be altered by adjusting the value of algorithmic parameter Δ. An expression for the fuzzy minimum energy membership function is given by Equation (9).

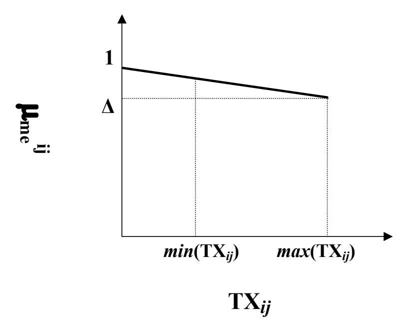


Fig. 3. A representation of fuzzy minimum energy membership function.

$$\mu_{me}^{ij} = 1 \quad + \quad \frac{(\Delta - 1) \times TX_{ij}}{max(TX_{ij})} \tag{9}$$

where

$$max(TX_{ij}) = \max_j \{TX_{ij}\} \;\; \forall \; j \; s.t. \; v_j \in N_i \tag{10}$$

$$min(TX_{ij}) = \min_j \{TX_{ij}\} \;\; \forall \; j \; s.t. \; v_j \in N_i \tag{11}$$

In order to formulate a fuzzy multiobjective aggregation function for an edge, the following fuzzy rule is proposed:

IF an edge
  has start node with high lifetime **AND**
  requires low energy consumption
THEN it is a *good* edge.

The above fuzzy rule translates to the following 'and-like' function by employing the OWA operator:

$$\mu^{ij} = \beta \times \min(\mu_{lt}^{ij}, \mu_{me}^{ij}) + (1-\beta) \times (\frac{\mu_{lt}^{ij} + \mu_{me}^{ij}}{2}) \quad (12)$$

where μ^{ij} is the fuzzy multiobjective membership of the edge $e(v_i, v_j)$ and $\beta \in [0, 1]$ is a constant. As can be observed, the above OWA function due to the term $\beta \times \min(\mu_{lt}^{ij}, \mu_{me}^{ij})$, asserts a preference on the objective having the least membership value. Also it may be noted, that due to nature of our carefully designed membership functions, the minimum value of μ_{lt}^{ij} is 0, whereas that of μ_{me}^{ij} is $\Delta > 0$. Therefore it is easy to infer, that if the residual energy (and the corresponding lifetime membership μ_{lt}^{ij}) is high, a *similar* preference level is given to both the objectives; otherwise if $\mu_{lt}^{ij} < \Delta$, the preference shifts to the maximum lifetime objective. As a conclusion, the value of parameter Δ affects the relative preference of the two routing objectives.

G (V, E) is the given directed graph
For each routing request $\boldsymbol{r_h(s_m, t_n)}$
  For each edge $\boldsymbol{e(v_i, v_j)}$ in **V**
    Compute fuzzy lifetime membership value $\boldsymbol{\mu_{lt}^{ij}}$
    Compute fuzzy min. energy membership $\boldsymbol{\mu_{me}^{ij}}$
    Compute multiobjective membership $\boldsymbol{\mu^{ij}}$
    Assign weight $\boldsymbol{w_{ij} = 1 - \mu^{ij}}$
  End For
  Find minimum weight path $\boldsymbol{p_h}$ from $\boldsymbol{s_m}$ to $\boldsymbol{t_n}$
  Send data along path $\boldsymbol{p_h}$
  Compute the minimum node energy in **G (V, E)**
  IF a node has run out of energy, stop.
End For

Fig. 4. A description of the proposed fuzzy multiobjective (FMO) routing algorithm.

The proposed fuzzy multiobjective routing algorithm (Figure 4) operates as follows: When a routing request $r_h(s_m, t_n)$ is initiated, a fuzzy lifetime membership is computed for each edge using Equation (6). Also, a fuzzy minimum energy membership for each edge is computed using Equation (9), followed by computation of a multiobjective membership using Equation (12). Then a weight is assigned to each edge using Equation (13).

$$w_{ij} = 1 - \mu^{ij} \quad (13)$$

Following the weight assignment, the multiobjective path p_h between s_m and t_n is found using Dijkstra's shortest path algorithm [8].

IV. Experimental Results and Discussion

Our experimental setup consists of 2-dimensional grid of size $X \times Y$ populated with randomly deployed n sensor nodes. In our experiments, sink node(s) are assumed to have infinite energy (powered by a fixed power source) and predetermined location(s), whereas all other nodes (including the source nodes) have an equal level of initial residual energy equal to σ. In the scope of a routing algorithm, we assume a perfect MAC layer with no energy losses due to retransmission attempts (it may appear to be an optimistic assumption considering typical wireless MAC protocols that offer a probabilistic nature of contention-based channel access mechanism but some recently proposed MAC protocols are able to offer deterministic contention-free channel access guarantees [5], [16]). Our traffic model is online, where there are no prefixed source nodes or predetermined traffic flows; rather we assume that any of the non-sink nodes on detecting an event in its sensing range is able to initiate a routing request in order to start sending its sensed data to a sink node.

As described in Section II, there are a number of simulation parameters to which, we need to assign suitable values. For wireless medium related parameters including A, B and m, we used typical values. A list of all the simulation parameters and their values is given in Table I.

TABLE I
A LIST OF VALUES USED FOR VARIOUS SIMULATION PARAMETERS.

σ	$1\ J$
A	$100\ nJ/bit$
B	$50\ pJ/bit/m^4$
m	4
X	25
Y	25
n	$\{30, 40, 50, 60, 70, 80, 90, 100\}$
r_t	$[7, 15]$

In addition, we have few algorithmic parameters (α and γ) for which the best values (e.g., those resulting in the maximum obtained lifetime) must be determined empirically. For this purpose, we experimented with numerous possible combinations of values for $\alpha \in [0.1, 0.9]$ and $\gamma \in [0.1, 0.9]$ using various values of n and r_t. In summary, the overall best value found for γ was 0.9, and hence we used this value for the rest of our simulations. Then, we conducted a series of experiments to determine the best value for α, and based on the results shown in Figure (5), its value is set at 0.2 for the rest of simulation runs.

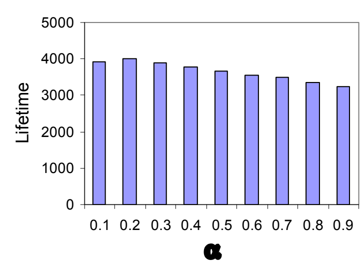


Fig. 5. Effect of α on the obtained lifetime results.

For the comparison purpose, we implemented the Online Maximum Lifetime (OML) heuristic [14]. A brief description of the algorithm follows: Let $G(V, E)$ be the given graph, and $G'(V, E')$ be the graph after removing all edges $e(v_i, v_j)$ such that $ce(v_i) < TX_{ij}$. For a routing request to send data from a source s_m to a sink t_n, the minimum energy path P' is found, and the minimum residual energy $minRE$ along P' is computed. A second pruned graph $G''(V, E'')$ is obtained by removing all edges $e'(v_i, v_j)$ from G' such that $ce(v_i) - TX_{ij} < minRE$. The weight w'' to be assigned to each edge in G'' is computed using the following equation.

$$w'' = (TX_{ij} + \rho(v_i)) \cdot (\lambda^{\eta(i)} - 1) \quad (14)$$

where λ is an algorithmic parameter of OML, and $\rho(v_i)$ is given by

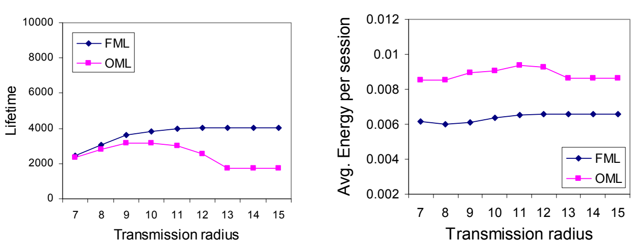
$$\rho(v_i) \quad = \quad \begin{cases} 0 & if \;\; ce(v_i) - TX_{ij} > eMin(v_i) \\ c & otherwise \end{cases} \qquad (15)$$

where $eMin(v_i)$ is the energy required by node v_i to transmit to its closest neighbor and '$c > 0$' is an algorithmic parameter. It may be noted that OML requires two shortest path searches per routing request.

In our implementation of OML, we used the best value for the parameter $\lambda = 10^{11}$ as reported by the authors. For a fair and reliable comparison, in case of both approaches, every result shown is averaged over 10 network topologies, whereas 10 random request sequences were generated for each topology. The performance metrics used for comparison are network lifetime and average energy consumption.

A. Performance comparison between FML and OML

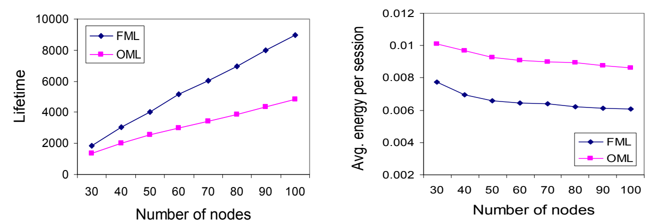
We start with investigating the effect of transmission radius on the network lifetime. Figures (6) (a) and (b), respectively, show the lifetime and the average energy consumption obtained by FML and OML in the case of 50 nodes for a range of transmission radius values. It may be noted that the lifetime obtained by FML initially increases until $r_t = 12$ and then becomes constant, whereas in case of OML lifetime reaches a maximum value at $r_t = 9$ and then falls sharply in interval $r_t \in [10, 13]$ until it attains a much lower constant value beyond $r_t = 13$. This behavior can be explained as follows: with the increase in r_t, each node is able to discover more neighboring nodes and thus a higher network connectivity is resulted that offers more routing choices at each node. As a result, the routing algorithm is able to find more cost-effective (maximal lifetime) routes. However at the same time, energy consumption also rises because a node now may transmit to a farther neighbor. Also in terms of energy consumption, it can be seen that for the entire range of transmission radius values, routes found by FML consume considerably lesser energy than those found by OML.



(a) (b)

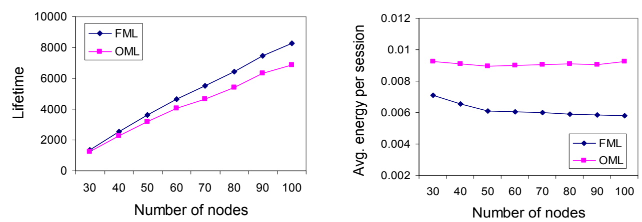
Fig. 6. A comparison of FML and OML in terms of (a) network lifetime and (b) average energy consumption for varying transmission radius (r_t).

Next, we study the effect of node density by randomly deploying $n \in \{30, 40, 50, 60, 70, 80, 90, 100\}$ sensor nodes in a region of fixed size. Figures (7) (a) and (b), respectively, show the lifetime and the average energy consumption obtained by FML and OML for a varying node density in case of $r_t = 12$. Since OML produced its best results, in terms of lifetime, at $r_t = 9$, hence for a fairer comparison, we repeat the above experiment by fixing $r_t = 9$ and the results obtained are shown in Figures (8) (a) and (b). It may be seen for both values of r_t that FML was able to obtain higher lifetime values and proved to be more energy frugal. Moreover, with the rising node density, FML shows a consistent increasing trend in the obtained lifetime regardless of the transmission radius used. On the other hand, OML is not able to show a similar increasing trend at higher transmission radii and its performance lag is more evident at $r_t = 12$. Also, it should be noted, that for both values of r_t, FML exhibits a continuously decreasing trend in terms of energy consumption as the node density grows, whereas OML exhibits a rather flat trend in case of $r_t = 9$.



(a) (b)

Fig. 7. A comparison of FML and OML in terms of (a) network lifetime and (b) average energy consumption per session for varying node density n in case of $r_t = 12$.



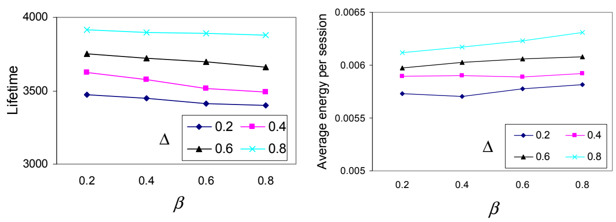
(a) (b)

Fig. 8. A comparison of FML and OML in terms of (a) network lifetime and (b) average energy consumption per session for varying node density n in case of $r_t = 9$.

Moreover, we conducted a set of experiments to obtain an insight into energy consumption patterns for the topologies used in our experiments. We found that FML behaves better than OML even in this comparison. Interested readers are referred to a more detailed report [12] that presents a discussion of those results.

B. FMO Performance: Effect of Multiobjective Routing on the Lifetime and the Energy Consumption

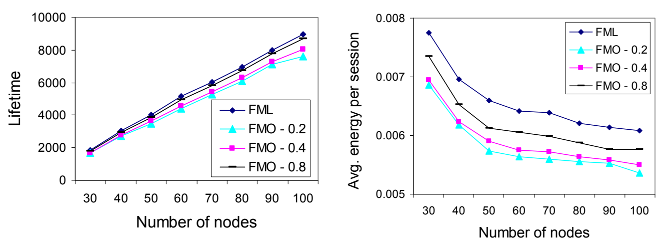
In this section, we present the results of FMO approach with a view of studying the effect of incorporating the minimum energy consumption objective on the lifetime maximization process. To start with, a series of experiments were conducted for determining suitable values for the parameters Δ and β using various combination values for the two parameters, and the lifetime and the average energy consumption values obtained from FMO are shown in Figures (9) (a) and (b), respectively. As may be observed, $\beta = 0.2$ results in the maximum lifetime as well as the least energy consumption, hence we set its value at 0.2 in all the subsequent runs. Also it may be noted that for smaller values of Δ, the preference of the energy consumption objective is high, and as a consequence, the average energy consumption is low, but at the same time, the network lifetime also falls. Hence, there is a visible tradeoff between the two routing objectives, and the parameter Δ can be used to achieve a desired balance.



(a) (b)

Fig. 9. (a) Lifetime and (b) average energy consumption obtained from FMO using various value combinations for the parameters Δ and β.

Next, we conduct experiments to study the effect of Δ in a scenario of varying node density. Figures (10) (a) and (b) show the lifetime and the average energy consumption, respectively, obtained by FML and FMO (for $\Delta \in \{0.2, 0.4, 0.6, 0.8\}$) for a varying node density n. Again a lifetime-energy consumption tradeoff is clearly visible in the results, i.e., for instance, FMO obtains the least energy consumption when $\Delta = 0.2$, but also obtains the least lifetime in this case. Thus, FMO is able to offer a flexible control over choosing a desired balance between the two routing objectives.



(a) (b)

Fig. 10. (a) Lifetime and (b) average energy consumption obtained from FMO using various values for the parameter Δ for varying node density n.

V. Related Work

Comprehensive reviews of existing routing techniques for WSNs have been presented by Perillo, et al. [15] and by Al-Karaki and Kamal [2]. The work that is most closely related to our work is the Online Maximum Lifetime routing scheme due to Park and Sahni [14]. Other solutions [4], [11], [17], [13], [9] either have assumptions that make them unsuitable for online routing or significantly under-perform in comparison to OML (and, as a consequence, the schemes we propose). For brevity, we do not present a detailed discussion of related work in this article. Interested readers are referred to a more detailed report [12] that presents greater discussion of related work.

VI. Conclusions

In this paper, the maximum lifetime routing problem in WSNs is addressed and two fuzzy routing algorithms are proposed. Experimental results are presented to show that the proposed algorithms are superior to the online maximum lifetime (OML) algorithm. We believe that the use of fuzzy functions and operators provides a promising direction for devising efficient solutions to numerous related energy aware routing problems in WSNs. The routing mechanism in the proposed algorithms is centralized due to the underlying centralized Dijkstra's algorithm, however the distributed versions can be obtained by employing any distributed shortest path algorithm.

In the immediate future, we will extend our work on multi-objective routing to include other crucial metrics such as latency and capacity. Further, we will consider flow prioritization to determine schemes for dropping certain requests when more important requests arrive. Other aspects of interest include context-aware routing and co-design of energy-efficient routing and MAC protocols using fuzzy functions, and the study of fuzzy functions in the broader context of management and provisioning of sensor networks.

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