Fuzzy Logic-based Routing Algorithm for Lifetime Enhancement in Heterogeneous Wireless Sensor Networks

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***Abstract*—Energy consumption of sensor nodes is a key factor affecting the lifetime of wireless sensor networks (WSNs). Prolonging network lifetime not only requires energy efficient operation, but also even dissipation of energy among sensor nodes. On the other hand, spatial and temporal variations in sensor activities create energy imbalance across the network. Therefore, routing algorithms should make an appropriate trade-off between energy efficiency and energy consumption balancing to extend the network lifetime. In this paper, we propose a Distributed Energy-aware Fuzzy Logic based routing algorithm (DEFL) that simultaneously addresses energy efficiency and energy balancing. Our design captures network status through appropriate energy metrics and maps them into corresponding cost values for the shortest path calculation. We seek fuzzy logic approach for the mapping to incorporate human logic. We compare the network lifetime performance of DEFL with other popular solutions including MTE, MDR and FA. Simulation results demonstrate that the network lifetime achieved by DEFL exceeds the best of all tested solutions under various traffic load conditions. We further numerically compute the upper bound performance and show that DEFL performs near the upper bound.**

***Index Terms*—Minimum-cost routing, lifetime maximization, fuzzy logic, energy consumption balancing, distributed shortest path routing, wireless sensor networks.**

I. Introduction

WIRELESS sensor networks (WSNs) are considered as one of the key enablers to the Internet of Things (IoT) era. A WSN comprises of a number of spatially distributed sensor nodes, which are used to monitor environmental conditions for various metrics, such as temperature, pressure, noise, vibration, as well as detecting object motion or existence of pollutants. In addition to sensing, these nodes have basic processing capabilities, and make wireless transmissions to deliver collected data to one or more data sinks, either over a single hop or over multiple hops. With these capabilities, WSNs can support a wide range of applications, such as military target tracking and surveillance, natural disaster relief, biomedical health monitoring, smart cities, hazardous environment monitoring, and seismic sensing [1].

In order to support a large deployment of a WSN and/or enhance the accuracy/precision of collected data in a target area, there has been a need to deploy a large number of sensor nodes. Furthermore, recent advances in Micro-Electro-Mechanical Systems (MEMS) technology has made it possible to reduce both the size and the cost of sensors, enabling large WSN deployments. On the other hand, these small and simple sensors have limited energy resources and processing capabilities, as well as short communication ranges. Moreover, in large scale network deployments, it is neither practical nor feasible to replace or recharge sensor batteries.

When sensor nodes deplete their batteries, this results in coverage holes in the network, i.e. such nodes become non-operational and can no longer collect data. This also leads to connectivity loss at parts of a WSN, as communications paths may be broken as a result of node failure events. In this respect, energy efficiency of a node operation is crucial and essential in WSNs. To prolong network lifetime, WSN communication protocols, which usually account for a large proportion of energy consumption of a node, must be energy-efficient. The lifetime of the network is defined in the literature as the time elapsed till the first node in the network dies i.e. depletes its energy [2].

While focusing on energy efficiency alone minimizes the energy consumption of individual sensor nodes, it does not guarantee an even distribution of energy consumption across all sensors in the network. Energy consumption balancing (ECB) is an important feature to achieve maximum network lifetime, where ideally all sensor nodes should consume energy such that they reach the end of their operational lifetime at the same time. In WSNs, multi-hop communication is widely adopted to achieve energy efficiency by ensuring short range transmissions. On the other hand, this mode of communication may also induce an energy imbalance across a WSN, as multi-hop communication paths naturally cause an unequal communication load on sensors, especially higher on those sensors closer to the data sinks. As such, in order to maximize a WSN's lifetime, besides reducing transmission ranges via multihop communication paths, it is also necessary to balance energy consumption in the WSN. Therefore, mechanisms and algorithms that ensure uniform energy dissipation are highly desirable in order for a WSN to remain fully functional for the maximum possible time period.

Numerous studies have proposed different ECB mechanisms, based on various network configuration and application types. These mechanisms have been summarized and compared in a comprehensive survey paper [2], which classifies ECB mechanisms into three groups:

1) Node deployment mechanisms: The basic idea of these

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mechanisms is to control node placement by deploying more sensor nodes or by adding some heterogeneous nodes in locations where traffic load is relatively high and energy consumption is relatively intense. Other mechanisms propose different sink node deployment options to attain energy balance in the network, such as deploying multiple data sinks in different locations or deploying a single mobile sink node. However, these mechanisms are not feasible in many applications, in addition to the high cost associated with them. Deployment time optimization needed in these mechanisms is another issue that limits their applicability.

2) Load balancing mechanisms: These mechanisms include unequal clustering, ECB routing, operation scheduling, and topology and transmission power control. The common aim is to evenly distribute the communication load among all sensors so that energy consumption is balanced and network lifetime is prolonged. Although they are generally easy to deploy, these mechanisms cannot realize global ECB due to the many-to-one communication pattern that is unavoidable without using node deployment mechanisms. Since all of the load balancing mechanisms are generally applicable without additional requirements, they are the most commonly deployed ECB mechanisms.
3) Energy mapping and monitoring mechanisms: These techniques produce a snapshot of energy distribution in the network and provide early warnings of network failures so that preventive actions can be taken to prolong network lifetime. However, periodic updates on node residual energy levels are required, which cause extra message overhead and hence energy inefficiency. Also, in forecasting-based monitoring, system convergence may take a long time.

In data gathering applications, sensor nodes continuously sense their environment and transmit the sensed data to a sink node in a cooperative manner. In multi-hop networks, this cooperation in data collection leads to sensors relaying not only their own collected data but also the data they receive from other nodes. Data forwarding is based on routing protocol used by sensors to pick which of their neighbours they need to forward their data to. This eventually affects the load on sensors; the more data a node receives, the more transmissions it makes. Hence, an effective and energy-efficient routing protocol is required to establish a route from each node to the sink. The overall performance of a WSN, in terms of energy consumption and network lifetime, highly depends on the WSN's routing strategy. Routing protocols that aim at maximizing network lifetime should be designed to make an appropriate trade-off between energy efficiency and energy consumption balancing in order to successfully extend the network lifetime.

Extensive research has been dedicated to maximum lifetime routing in multi-hop wireless sensor networks. These routing strategies can be widely categorized into optimization-based and shortest path (or minimum cost) methods [3]. In the optimization-based methods, routing is modelled as a network flow problem with the assumption that data transmitted by a node can be divided arbitrarily between the nodes on the selected routes to the sink. These methods greatly improve lifetime, however, they are not feasible for distributed implementation which limit their practicality [3]. On the other hand, shortest path methods support distributed implementation. These methods assign energy-related cost values to all the links of the network and then utilize shortest path strategies, such as Bellman-Ford algorithm, to select the optimal routes with the minimum total cost. As link costs directly influence the route selection and the performance, the issue of designing an effective cost function, that calculates the cost of a link based on the network status, is vital for achieving the best performance [3].

While the shortest path methods offer distributed implementation, their effectiveness highly depends on the ability to capture and map network status into an appropriate abstractly defined cost function for shortest path computation. The research challenge is thus 1) the input metrics that can best describe the network status, and 2) the mapping and consolidation of various inputs into a single abstractly defined cost function.

In the aspect of input metrics, existing works often consider a certain network setup and focus on input metrics that can capture the status of the considered network. As a result, some of the proposed solutions work well in particular network setups but fail to deliver promising performance in other setups. For example, most existing works consider homogeneous nodes where all nodes have the same traffic generation process and battery capacity. However, in many applications, events could occur randomly or repeatedly at only a specific part of the network area [4]. Without capturing the difference in traffic generation process and/or battery capacity among the nodes, a routing protocol may misjudge the network status and over utilize a certain set of nodes for packet forwarding, leading to early exhaustion of their battery power [5]. Protocols such as Flow Augmentation (FA) algorithm [6] which does not capture the traffic load of nodes may repeatedly select nodes with high residual energy for data forwarding regardless of their high traffic generation. By the time these nodes are avoided due to low residual energy, their own high traffic load quickly depletes their energy much earlier than other nodes.

In the aspect of mapping and consolidation of various inputs, a well-designed cost function is a key to energy-efficient decisions and prolonged network lifetime. Proposed routing protocols for WSNs use fixed (crisp) metrics when making routing decisions. However, the relationship between an input value and its influence on the performance is often nonlinear. Directly using the crisp inputs in a linear manner may lead to improper routing decision. A proper nonlinear mapping of crisp input values to cost values is needed to address this issue. Moreover, different routing metrics influence the performance of the network lifetime to different extents depending on the network conditions. Certain metrics should be given more weight in routing decision under certain conditions. For example, remaining energy metric is more important when node's energy level is low. Emphasizing an inappropriate metric in the cost function computation can lead to significant

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performance issues. Since estimating the network dynamics can be difficult and costly, it is challenging to design an effective cost function that can provide optimum performance under various network operating conditions. The existing cost function based routing algorithms are merely designed according to designers' experience which results in arbitrary and suboptimal design [7]. Therefore, it is often difficult to justify the rational of their proposed cost function. Liu et al. [7] made an attempt to come up with design principles and guidelines for cost functions construction. This work presents a good analysis of cost function design and derives logical design guidelines. However, similar to other cost function based routing solutions, this work uses a rigid computation model when combining the routing metrics, which may lead to wrong decisions in absence of logic.

Designing appropriate mapping functions for various input metrics is not an easy task. However, we see opportunity in applying fuzzy logic for this purpose. FL has the potential of dealing with conflicting situations and nonlinearity in data, using heuristic human reasoning without the need for a complex mathematical model [8]. Despite the obvious advantages of FL and its wide and successful deployment in many fields, there is a limited number of routing algorithms that consider FL in their design. Many routing algorithms require only simple decision making process, and hence the use of fuzzy logic is unnecessary. However, for energy-aware routing demanding comprehensive decision making process, fuzzy logic represents an effective approach.

Motivated by the aforementioned shortcomings in the literature and the stated design challenges, we propose a novel Distributed Energy-aware cost function based routing algorithm (DEFL) that uses Fuzzy Logic approach to improve network lifetime in dynamic network conditions. We provide a generic framework for designing energy-related cost functions. Our algorithm includes energy consumption rate and node remaining energy metrics in its cost function. Energy consumption rate is represented by the combination of transmission energy and energy drain rate. Instead of using rigid computation model to blend different metrics, we apply soft human logic through fuzzy logic approach. We first use two fuzzy logic systems to map the crisp values of the metrics and then aggregate the costs using a weighted product function to produce the final link cost. A shortest path method, Bellman-Ford algorithm, is then used to determine the minimum cost route from any sensor node to the sink node. We evaluate the performance of our routing algorithm (DEFL) through extensive simulation using various performance metrics. The performance of our algorithm is compared with three well-known routing algorithms, i.e. MTE [9], FA [6] and MDR [10]. In addition, DEFL is compared to the optimal solution computed by our optimization solver. The simulation results demonstrate that DEFL indeed provides better performance than the evaluated algorithms in terms of network lifetime and energy balancing property. It consistently performs very close to the optimal performance obtained by the solver.

The main contributions of this paper are summarized below.

1) A generic formulation of the maximum network lifetime routing problem has been provided. A minimax optimization function, based on Matlab fminimax solver, is used to determine the upper bound lifetime performance of a given network configuration which we use as a performance benchmark.
2) A generic framework for designing energy-related cost functions is introduced. Based on the framework, a heuristic routing algorithm DEFL is proposed which combines cost function based routing and fuzzy logic approach to improve network lifetime at different network conditions. Appropriate energy metrics are combined using two fuzzy logic systems which apply soft human logic to blend different metrics. The performance of the proposed algorithm is demonstrated through simulation and compared with existing algorithms MTE, FA and MDR, as well as the upper bound calculated by the solver.

The rest of the paper is organized as follows: Section II reviews the related literature. Section III provides an overview of fuzzy logic approach. Section IV describes the sensor network model considered in our work. In Section V we formulate the maximum lifetime routing problem, and recommend a solver algorithm to derive an upper bound. Our proposed routing algorithm is presented in Section VI. In Section VII, we demonstrate the performance achieved by our proposed algorithm in comparison to existing heuristic routing mechanisms, as well as the maximum lifetime obtained by the solver. Finally, some concluding remarks are made in Section VIII.

II. Related Work

Significant efforts have been devoted to developing energy efficient and energy consumption balancing routing algorithms with the objective of extending the lifetime of sensor networks. In this section, we review the most relevant energy-aware minimum cost routing algorithms that are based on either predefined cost function computation or fuzzy approach.

A. Cost Function Based Routing Algorithms

The minimum total energy (MTE) routing approach was proposed in [11] and [9]. This approach minimizes the total consumed energy to reach the sink. However, if all the traffic is routed using the minimum energy route, the nodes on that route will deplete their energy quickly causing network partition while other nodes still have plenty of energy. Therefore, since MTE does not consider the remaining energy of the nodes, it cannot effectively extend the lifetime of the network.

Min-Max Battery Cost Routing, MMBCR, proposed by Singh et al. [12] considers as its metric the residual battery capacity. The nodes with high battery capacity are allowed to take on routing tasks more often than the nodes with low battery capacity. MMBCR extends the lifetime of the nodes without guaranteeing that the total consumed energy is minimized over the selected route. The Conditional Min-Max Battery Cost Routing (CMMBCR) [13] considers both the minimum total energy consumption of routes and the remaining energy of nodes. This approach does not guarantee that the nodes with high remaining energy will survive when

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they have heavy traffic passing through them. Hence, the minimum drain rate (MDR) mechanism was proposed by Kim et al. [10] which introduced a new metric, the drain rate. This metric is incorporated with the residual energy of a node to predict its lifetime according to current traffic conditions. Routing protocols based only on metrics related to the remaining energy cannot be used to establish the best route. If a node, due to its high remaining energy, accepts all route requests, much traffic load will be passing through the node causing sharp reduction in its battery energy. This could result in the node exhausting its energy very quickly and die. Therefore, a metric that is based on the traffic load characteristics is required for an efficient cost function.

MDR, however, does not guarantee that the total transmission energy is minimized over a chosen route. A modified version is further proposed by the same authors, which is called Conditional Minimum Drain Rate (CMDR). This mechanism is based on choosing a path with minimum total transmission energy among all the possible paths. The set of possible paths is constituted by nodes that satisfy a lifetime threshold, which represents how long each node can sustain its current traffic with its remaining battery energy and drain rate without energy breakage. Proper choice of the threshold value greatly influences the performance of this mechanism.

Chang and Tassiulas in [6] proposed, Flow Augmentation (FA) algorithm, a shortest path routing algorithm for maximizing network lifetime based on link costs that reflect both the required communication energy and the residual energy levels. This algorithm does not consider the node's traffic load in the route selection process. In addition, the performance of this approach depends greatly on the empirical values assigned to the parameters.

A distributed energy balanced routing (DEBR) protocol is proposed in [4]. Similar to FA, this algorithm uses a combination of the required communication energy and the available energy to find an optimum routing path that achieves energy balance. Each sensor determines whether it is less costly to send the intended traffic to one of its neighbours or directly to the base station. This work considers a special case of networks in which all sensors can reach the sink directly.

Liu et al. [7] proposed two energy-aware cost function based routing protocols. The Exponential and Sine Cost Function based Route (ESCFR) maps a small change in remaining nodal energy to a large change in the cost value. Meanwhile, the Double Cost Function based Route (DCFR) considers the energy consumption rate of nodes in addition to their remaining energy. This new cost function accounts for the high energy consumption rates experienced by nodes in the hotspots, hence it further improves the energy balancing performance of the protocol.

In [3], Habibi et al. provide a framework to analytically derive the best achievable performance that can be obtained by any distributed routing algorithm based on the shortest path approach. The proposed framework can be used as a benchmark to evaluate the energy efficiency of the existing routing algorithms. The computational complexity of multi-parametric programming used in this approach grows exponentially with the number of links in the network. Therefore, for large networks the proposed approach becomes unreasonable.

In a recent work [14], the authors propose a new energy-cost function and a new end-to-end delay function which are used to determine the lowest cost route from cluster heads to the sink. This work aims to achieve the best trade-off between minimizing energy consumption and minimizing delay in cluster-based multi-hop routing.

B. Fuzzy Logic Based Routing Algorithms

The potential of fuzzy logic has been fully explored in many fields including signal processing, speech recognition, aerospace, robotics, embedded controllers, networking, business and marketing [8]. Moreover, the use of FL in WSNs is shown to be a promising technique since it allows combining and evaluating diverse parameters in an efficient manner. FL is a good approach as its execution requirements can be easily supported by sensor nodes, while it is able to improve the overall network performance. In WSNs, fuzzy logic has been used in localization, clustering and cluster head election, routing, data aggregation, security, etc [15].

The use of FL to improve the LEACH protocol, LEACH-FL, is proposed in [16]. Combining node density, distance and residual energy using FL, resulted in improved decision making for cluster head selection. In [17], an energy-aware distributed dynamic clustering protocol (ECPF) is proposed, in which FL is employed to evaluate the fitness of a node to become a CH. Both node degree and node centrality are taken into account to compute fuzzy cost.

A recent research article [18] describes a new method called SMF which is a multi-hop clustering routing algorithm that aims at prolonging the WSN lifetime. The proposed approach combines a clustering method named LEACHEN, a multi-path algorithm and a fuzzy approach to select the optimal routing path from the source to the destination. This method considers the residual energy of nodes, the number of hops and the traffic load as the routing metrics.

Although there are a number of research works that utilize fuzzy logic to optimize cluster head election, in the field of flat routing, the use of fuzzy logic has not been studied extensively.

AlShawi et al. [19] propose a routing method to extend network lifetime using a combination of a fuzzy approach and an A-star algorithm. This method is based on central computation of routing schedules by the base station. Hence, it requires the nodes to send periodic updates of their remaining energy level and traffic load to the base station which in turn calculates optimal routing schedule and broadcast it.

Haider et al. propose in [8] an energy aware routing mechanism based on fuzzy logic. In this mechanism, the gateway is responsible for setting up of routes for sensor nodes and for the maintenance of centralized routing table that indicates the next hop for each sensor node. Gateway uses fuzzy logic to determine the cost of link between any two sensor nodes through input variables, such as transmission energy, remaining energy, and queue size. Once the costs of all possible links to the gateway are computed, the route will be determined using the shortest path algorithm. According to this method, avoiding nodes that have remaining energy

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of less than 40 per cent of their initial energy extends the network lifetime. As with the previous work, this approach is centralized, thus is not suitable for large networks.

Approaches proposed in [20] and [21] are other examples of research efforts exerted towards making use of fuzzy logic in addressing maximum lifetime routing problem.

In [22], a novel routing protocol is proposed for VANETs called Adaptive Fuzzy Multiple Attribute Decision Routing (AFMADR). Four attributes are used to characterize the candidate vehicles which form inputs to fuzzy mapping systems. A proposed adaptive weight algorithm is used to calculate weights of the attributes to enhance the scalability and robustness of the AFMADR scheme. This recent work is another example of utilizing human logic through fuzzy approach in routing decisions.

These existing works reinforce the application of fuzzy logic as a useful technique to improve the performance of routing protocols. Meanwhile, they indicate a room for further research.

III. Overview of Fuzzy Logic Approach

Fuzzy logic (FL) was first proposed by Lotfi-Zadeh [23] and is used to model human decision making behaviour. Fuzzy system imitates the logic of human thought, which is much less rigid than the calculations generally performed by computers.

FL offers several unique features that make it a particularly good approach for many control problems. It has the ability to handle uncertainty and ambiguity and allows the combination of multiple, and often conflicting, parameters into one single metric. Additionally, FL has the advantages of ease of implementation, robustness, and ability to process non-linear systems [24].

Fuzzy logic analyzes information using fuzzy sets. Each set is represented by a linguistic term such as ”Far”, ”Warm”, ”High”, etc. A fuzzy set is used to describe the input and output fuzzy variable and is characterized by a membership function. The membership function represents degree of belongingness of each crisp input x to fuzzy set F. It provides mapping of each input value to a membership value in the interval [0 .1], where a membership value close to 1 indicates that the input belongs to the fuzzy set with a high degree, while small membership values mean that this fuzzy set does not suit this input very well.

In fuzzy systems, a set of linguistic rules are used to express the input-output relationship. Fuzzy rules are the heart of a fuzzy system and they characterize the dynamic behaviour of a system. They are defined based on the knowledge of a human expert or can be extracted from numerical data. The rule base is basically a collection of IF-THEN statements. The part before THEN is called antecedent and forms the fuzzy input space, while the part following THEN is referred to as consequent and forms the fuzzy output space. In the case of a fuzzy rule having more than one antecedent (conditional element), logic operations such as AND or OR is used to combine fuzzy sets and estimate the output value of rule evaluation. All the rules are evaluated in parallel. Any rule that get triggered contributes to the final fuzzy solution space.

A fuzzy system basically consists of four components namely; fuzzification, rule base, inference engine and defuzzification.

The input to the fuzzy system is usually a crisp -numeric- value. Fuzzification is the process of converting the crisp input into a suitable set of linguistic values ”fuzzy Sets” and assigning it a degree of membership to each fuzzy set. Most common membership functions are triangular, trapezoidal and Gaussian. These fuzzy values represent the membership values of the input variables to the fuzzy sets. The fuzzified values activate the rules to produce a fuzzy output. The inference engine is used to determine the manner in which the consequent fuzzy sets are aggregated to form the final fuzzy solution space. The fuzzy output is sent to the defuzzifier which maps it to a crisp number that can be used for making decisions or to control actions. Common defuzzification techniques are centroid, composite maximum and composite mass. Interested reader can refer to [23] and [25] for more details on fuzzy logic approach.

IV. Sensor Network Model

In this study, the network is composed of n heterogeneous sensors randomly and uniformly distributed over a target monitoring area. Nodes are capable of activity sensing and data collection, data processing, and communication. Each node has an initial amount of battery energy which is limited and mostly consumed in transmission and reception at its radio transceiver. As in typical deployments, it is considered that nodes are left unattended after deployment; therefore, battery recharge or node replacement is not possible. Nodes can adjust the amount of transmission power by using power control methods so as to minimize power consumption. Nodes are not equipped with GPS equipment and hence they are location-unaware. Distance is estimated based on Reference Signal Received Power (RSRP). Sensor nodes are quasi-stationary. All sensed data must be transmitted to the sink node. The sink node does not have hard limitations on energy, memory resources, and computational power.

A. Network Topology

Sensor nodes deliver their sensed data to the data sink over multihop paths, which are formed as a result of next hop choices made by nodes independently, i.e. using a distributed routing algorithm. The choice of a particular next hop influences a nodes transmission power consumption, hence its energy efficiency in routing.

Sensor nodes that can receive a nodes packet transmission, when using its maximum transmission power, are referred to as its *neighbours*. Nodes exchange control packets with their neighbours to provide updated information on their energy status. Such updates ensure the availability of the required information for nodes to independently make their routing decisions.

Since sensor nodes running a duty-cycled medium access control (MAC) protocol turn their radios off during idle periods to save battery energy, there is a need for coordinating their active/sleep time periods, by means of ensuring that neighbouring nodes are synchronized [4].

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B. Traffic Model

The majority of studies in the current literature of WSN routing algorithms assume that all network nodes have uniform data generation rates [4]. In monitoring applications, this assumption generally holds, as sensors perform sensing tasks at regular time intervals and hence they have similar data generation rates. However, in many applications, this assumption becomes unrealistic. For instance, in event-triggered sensing tasks, which are common in applications such as target tracking and forest fire detection, it is not uncommon to observe high data generation rates at particular nodes located in the vicinity of the event. Therefore, in order to evaluate the robustness of a routing algorithm, it is important to consider a diverse set of data generation patterns. As such, in this study, we consider the presence of two generation patterns: periodic and event-triggered. Traffic patterns can change from one type to the other over time.

C. Energy Consumption Model

For energy dissipation, we employ the model adopted in [6] in which energy required to transmit one unit of information from a node i to node j is given by

$$E_t(ij) = \beta_1 + \beta_2 d_{ij}^4, \tag{1}$$

where d_{ij} represents the distance between the two nodes, $\beta_1 = 50nJ/bit$ is the energy consumed to run the transmitter circuitry, and $\beta_2 = 100pJ/bit/m^4$ is the energy consumed at the transmitter amplifier. Here, the path loss exponent of 4 is used to represent the multipath reflection instead of using a free space model which uses 2. The energy required to run the receiver circuitry is assumed to be constant and specified as $\beta_3 = 150nJ/bit$.

D. Lifetime of Sensor Network

Unbalanced energy consumption is an inherent problem in WSNs, which is characterized by multi-hop routing and a many-to-one traffic pattern. This uneven energy dissipation can significantly reduce network lifetime [19]. Battery energy depletion at network nodes may cause network partitions, i.e. certain parts of the network may become disconnected, which is undesirable in WSNs, especially when it matters to collect data from all parts of the network to a data sink. Therefore, the lifetime of a WSN is a central parameter when evaluating the performance of routing protocols. In existing studies, the lifetime of a WSN is often defined as the period of time until the first node in the network completely depletes its energy and becomes non-functional. To prolong a networks lifetime, the goal is then to have an energy-efficient and energy-balancing routing algorithm in place.

V. Maximum Lifetime Routing Problem Formulation

In this paper, a WSN is modelled as a directed graph $G(V, E)$, where V is the set of all vertices (nodes) and E is the set of all edges (directed links) of the graph. A link (i, j) is said to exist if and only if $j \in N_i$, where N_i is the set of neighbouring nodes of node i. Each node i has an initial battery energy of E_i, and the data generation rate at node i is G_i.

In the following, we shall formulate the problem of the maximum lifetime for a sensor network $G(V, E)$ that can be achieved through its routing decisions. Let $L_{net}(\alpha)$ be the network lifetime and α be the corresponding set of routing decisions. Each decision is represented by α_{ij}, which describes the percentage of traffic that node i forwards to node j as assigned by the routing algorithm.

The lifetime of node i under a given routing decisions α is given by:

$$L_i(\alpha) = \frac{E_i}{E_i^{total}(\alpha)}, \tag{2}$$

where $E_i^{total}(\alpha)$ represents the total energy consumed by node i within a unit time. It is the sum of the overall receive energy E_i^{rx} and the overall transmit energy E_i^{tx} within a unit time.

$$\begin{aligned} E_i^{total}(\alpha) &= E_i^{rx}(\alpha) + E_i^{tx}(\alpha) \\ &= \sum_{k \in C_i} F_k \alpha_{ki} \beta_3 + (G_i + \sum_{k \in C_i} F_k \alpha_{ki}) \sum_{j \in P_i} \alpha_{ij}(\beta_1 + \beta_2 d_{ij}^4). \end{aligned} \tag{3}$$

Here, F_k denotes the traffic of node k within a unit time including the traffic generated by k itself and the traffic received from all its child nodes, i.e. nodes that forward their traffic to node k. The sets (C_i) and (P_i) collect the child and parent nodes of node i, respectively.

The network lifetime $L_{net}(\alpha)$ under routing decisions α can be defined as the minimum lifetime over all nodes, which is given by:

$$L_{net}(\alpha) = \min_{i \in V} L_i(\alpha). \tag{4}$$

Since all sensed data should be forwarded to the sink node, flow conservation condition at node i requires that the sum of data traffic generated by node i within a unit time and the total data by incoming flows must be equal to the total amount of data carried by outgoing flows. Therefore, the traffic equation for each node is:

$$\sum_{k \in C_i} F_k \alpha_{ki} + G_i = \sum_{j \in P_i} F_i \alpha_{ij}. \tag{5}$$

Consequently, the objective function can be expressed as follows:

$$\begin{aligned} &\max_{\alpha} \min_{i \in V} L_i(\alpha) \\ \text{s. t. } & 0 \leq \alpha_{ij} \leq 1, i \in V, j \in P_i \\ & \sum_{k \in C_i} F_k \alpha_{ki} + G_i = \sum_{j \in P_i} F_i \alpha_{ij}, i \in V \\ & \sum_{j \in P_i} \alpha_{ij} = 1. \end{aligned}$$

We seek *fminimax* solver from Matlab optimization toolbox to find α that maximizes network lifetime. The tool *fminimax* minimizes the worst-case value of a set of multivariable functions, starting at an initial estimate. It uses a Sequential Quadratic Programming (SQP) method to return the optimum solution.

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The maximum lifetime routing problem has been formulated in some existing works. In [6], the authors consider the network lifetime (denoted by T in their formulation) as an independent variable and use Linear Programming (LP) to determine the optimal solution. Meanwhile, another work [4], uses Integer Programming (IP) to determine the solution space. In our work, maximum lifetime routing problem is formulated in much more details to show the relation between the routing decisions, the traffic load distribution among different nodes and in turn the lifetime of each node. The recursive nature of this relation and the subsequent non-linearity is made clear in our formulation. Hence, we formulate a minimax objective function and use non-linear solver based on SQP method to determine the optimal routing solution.

VI. The Proposed Routing Algorithm-DEFL

In this work, we propose a heuristic Distributed Energy-aware Fuzzy Logic based routing algorithm (DEFL) to significantly improve the network lifetime of wireless sensor networks with heterogeneous nodes and variable traffic loads. Our algorithm is based on shortest path routing strategy with minimum cost. This strategy permits distributed implementation where each node gathers only local information to make independent routing decisions. This approach greatly reduces the communication cost and improves scalability.

As in typical minimum cost energy-aware routing algorithms, DEFL algorithm assigns energy related cost values to the network links, and then utilizes shortest path strategies to find a set of routes which yield the minimum total path cost from the source to the destination. The assigned link cost values are adaptively updated based on energy related inputs. We focus on instantaneous energy levels and energy consumption rates which are the key inputs to estimate the lifetime of the nodes. While the energy level gives direct information of present energy status of a node, the energy consumption rate provides movement of energy status which is influenced by the node operation including sensing, traffic generation, and others. To jointly utilize the inputs, a mapping mechanism is needed to map multiple inputs into a single cost value. Instead of using crisp values directly to compute the cost, here we use fuzzy logic approach for the mapping mechanism. Fuzzy logic can easily unify units of different inputs. Besides, it has the ability to deal with conflicting inputs. The design also involves human logic which provides more rational decision making. Our proposed algorithm DEFL has the following features:

1) It is a distributed algorithm. All the components of the algorithm-shortest path algorithm and fuzzy logic-are amenable to distributed implementation. Each node utilizes local knowledge from its one hop neighbours to make independent routing decisions resulting in a more scalable and energy efficient solution.
2) It is adaptive to network conditions. Link cost values are dynamically computed and assigned to reflect the spatial and temporal variation in node operations and traffic conditions. Optimal routes are always sought by periodic route recalculation.
3) It is flexible to cope with various inputs. Our design utilizes fuzzy logic approach where inputs and rules can be easily redefined and tuned making the system design flexible.

The commonly used Bellman-Ford algorithm is employed in our work for the shortest path computation to determine the minimum cost route from any sensor node to the sink node. The Bellman-Ford algorithm is implemented in a distributed manner. We revisit its operation as follows. In Bellman-Ford algorithm, each node computes its own best cost estimate to reach the sink node. This estimate is referred to in the literature as the sink access cost value. Each node begins its operation by initializing the sink access cost value which is set to zero for the sink node and to infinity for any other node. Each sensor node determines the cost of the links to all of its neighbours which are called the link cost values and are denoted by w_{ij} for all $j \in N_i$. In the next stage of the algorithm, each node shares its sink access cost value, denoted by S_i for node i, to its neighbouring nodes. This value is updated by every node in each iteration as $S_i = \min_{j \in N_i}(w_{ij} + S_j)$. The iterations lead to the optimal sink access cost values and the index of the best next hop node is obtained [3].

A. Metrics Used in our Algorithm

Here we present the different inputs we use in DEFL algorithm:

1) Transmission energy. This metric measures the amount of energy needed to perform a transmission. It is used to ensure that messages are sent through energy efficient paths in order to keep the total energy needed to route the message to a minimum. Due to sensors limited energy, the routing algorithm should be designed to find paths consuming the least amount of energy to prolong the lifetime of the sensor network. The node that can be reached with the least transmission energy is a good candidate for the optimal route.
2) Remaining energy. This metric measures the instantaneous battery level of a node. To avoid depleting the energy reserves of energy efficient paths, the remaining energy of the node should be considered in the routing decisions. A routing protocol that uses this metric would favour a path that has the largest total energy capacity from source to destination.
3) Energy drain rate. This metric measures the rate at which the energy is consumed over a time period. A node consumes energy for various operations. Communications consume significant amount of energy compared to other operations. The amount of energy consumed in communications is directly influenced by the amount of traffic. The traffic of a node includes the traffic generated by its own application and the traffic received from neighbouring nodes for forwarding. Since a node with high residual energy will be used frequently for forwarding traffic, its battery energy will experience a sharp drop. Moreover, in a network where concentration of events in particular sub-areas occurs, the sensor nodes covering these areas experience high traffic load causing

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rapid drainage of their battery energy. The rapid drop of battery energy of some individual nodes may cause them to quickly run out of energy which in turns affects the proper network operation. This problem can be mitigated by employing metrics that capture traffic load characteristics such as the energy drain rate [10]. A routing protocol using this metric would select a path that has the lowest total traffic load.

B. Design of the Proposed Cost Function

In cost function based routing algorithms, a well designed cost function is a key to energy efficient decisions and prolonged network lifetime. Our objective is to design an optimum cost function which will achieve network lifetime maximization in networks with heterogeneous nodes i.e. nodes with different initial battery capacity, and operate under variable traffic conditions.

In general, a cost function design should consider the following two aspects: (i) which inputs should be used in the cost function computation, (ii) how these inputs can be aggregated to produce a final cost value. Changes in the network operating conditions, such as spatial and temporal variation in traffic load, make it challenging to design an effective cost function. Different routing metrics influence the performance of the network to different extents depending on the traffic and energy states of the nodes. Accordingly, the most influencing metric, at certain operating condition, should be given more weight in routing decisions than other metrics. Therefore, properly designed cost function should enable the routing process to automatically adapt to the changes in the environment.

As discussed earlier, we consider instantaneous energy levels and energy consumption rates as the two inputs. While instantaneous energy level is obtained directly by reading the residual battery energy, energy consumption rates are represented by the combination of transmission energy and energy drain rate. We design two mapping systems to convert input values to relay probabilities which are inversely related to the link cost values. Many techniques are available to perform this mapping process using the original crisp values. However, we propose fuzzy logic in our approach due to its effectiveness in combining multiple yet conflicting parameters and in imitating human logic in decision making. The outputs of both systems are then combined using a cost function. Our proposed approach provides a framework for designing energy-related cost functions. Fig. 1 illustrates our approach. Note that other existing solutions such as FA [6] and MDR [10] are special instances of the framework. FA considers two inputs namely the required energy for data transmission and the residual energy of the nodes. It uses a weighted product function to aggregate the two inputs and produce the final link cost. MDR considers two inputs namely the residual energy of the node together with the energy drain rate. Similarly, it uses a weighted product function to aggregate the inputs. In our solution, instead of using crisp values of the inputs to compute the cost, we first use fuzzy logic to map the crisp values of the inputs and then aggregate the costs to produce the final link cost. The two fuzzy logic based mapping systems will be described in the next subsection. In the following, we shall discuss the design of the final cost aggregation.

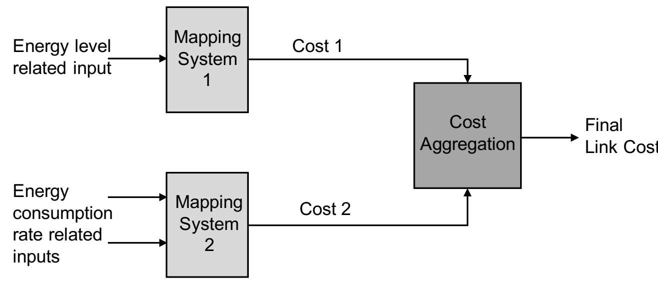

Fig. 1: Cost function design framework.

In our design, the routing metrics used in calculating the link cost w_{ij} are: the residual energy of node i, $RE(i)$, the energy consumed in transmitting a unit data over the link ij, $TE(ij)$ and the energy drain rate of node i, $DR(i)$. These metrics are normalized with respect to node initial battery capacity, maximum transmission energy and maximum energy drain rate among all neighbours, respectively. To maximize the minimum lifetime over all nodes, a route should be picked such that it consumes less total energy, avoids nodes with small residual energy and avoids nodes with high traffic load.

The two fuzzy logic based mapping systems produce relay probabilities which are then converted to costs inversely proportional to the probabilities. The two costs are aggregated using a weighted product function. Let $w_1(ij)$ and $w_2(ij)$ be the costs produced by the first and second mapping systems respectively, our proposed aggregation function is:

$$w_{ij} = w_1(ij)^{\tau} w_2(ij), \tag{6}$$

where τ is the normalized weight. In our solution, since cost describing residual energy, $w_1(ij)$, is more critical, we set $\tau > 1$. More analysis of τ setting is provided in Section VII-B.

C. Fuzzy System Implementation

As shown in Fig.1, the aim of the fuzzy mapping systems is to determine Cost 1 (or $w_1(ij)$) and Cost 2 (or $w_2(ij)$) of link ij. Fig. 2 shows the design of the two fuzzy systems. Fuzzy System 1 (FS1) deals with the energy level related input. It takes the normalized residual energy or $RE(i)$ of node i. It produces output variable $RP_1(ij)$, such that $w_1(ij) = \frac{1}{RP_1(ij)}$. Fuzzy System 2 (FS2) deals with the energy consumption rate related inputs. It takes two inputs including the transmission energy $TE(ij)$ consumed by node i to transmit to node j and the energy drain rate $DR(i)$ of node i. It produces output variable $RP_2(ij)$, such that $w_2(ij) = \frac{1}{RP_2(ij)}$.

Our proposed method uses five fuzzy sets (very high, high, medium, low, very low) for each input and output variable of both fuzzy systems. The membership functions for all inputs and outputs are identical and are described in Fig. 3. The domain of all input variables has been adjusted such that the universal of discourse is between 0 and 1, as can be noticed from the figure (x-axis). This allows the fuzzy sets to be applicable for any network configuration.

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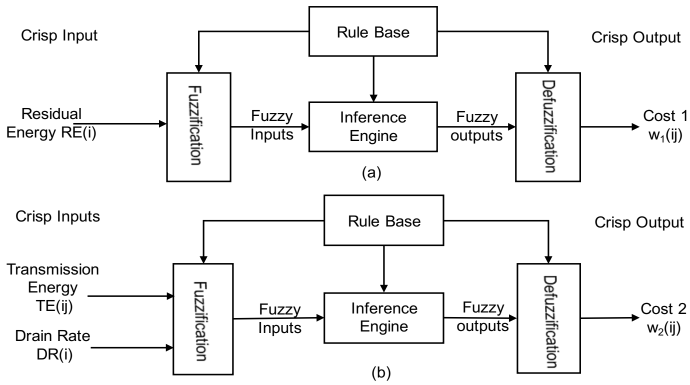

Fig. 2: Fuzzy systems (a) FS1, and (b) FS2.

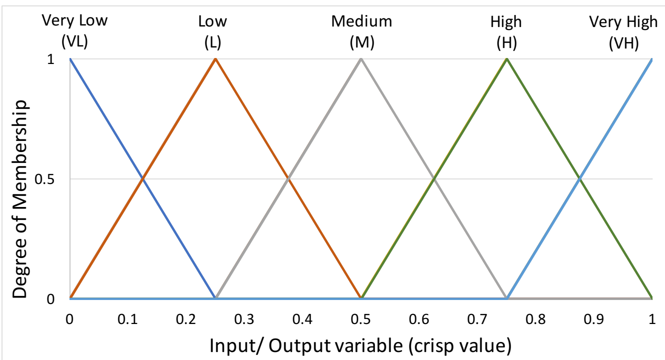

Fig. 3: The membership functions used for all input and output variables of both fuzzy systems.

In determining the link cost from node i to node j, the following input variables are used:

1) The normalized residual energy $RE(i)$ for FS1. It indicates the energy level of node i. Intuitively, nodes with low value of residual energy should be avoided as next hop nodes, hence its low value results in low value of relay probability $RP_1(ij)$, output of FS1, and accordingly high link cost $w_1(ij)$. In the total link cost calculation w_{ij}, this value is given additional weight using the parameter τ.
2) The transmission energy $TE(ij)$ for FS2. It represents the energy needed to transmit a data unit from node i to node j. Lower value of transmission energy gives link ij higher chances in being selected for data forwarding which means high relay probability $RP_2(ij)$, output of FS2, and accordingly low link cost $w_2(ij)$.
3) The energy drain rate $DR(i)$ for FS2. It indicates the rate of energy consumption of node i based on its traffic conditions. Nodes with high rate of energy consumption should be avoided as next hop nodes which results in low relay probability $RP_2(ij)$, output of FS2, and accordingly high link cost $w_2(ij)$.

Notice that the design presented for FS2 takes two inputs: transmission energy and energy drain rate and produces a corresponding relay probability. In some situations, these two inputs may result in conflicting outputs making it difficult to reach a perfect decision. For example, a certain node may be reached using a low transmission energy and hence results in

Table I: Fuzzy rules for FS1.

No.	Normalized Residual Energy (RE)	Relay Probability (RP_1)
1	Very Low	Very Low
2	Low	Low
3	Medium	Medium
4	High	High
5	Very High	Very High

high relay probability. Meanwhile, the same node might have a high drain rate making it less favorable as the next hop and hence leads to low relay probability. Our fuzzy approach is capable of combining these inputs and resolving any potential conflict through fuzzy rules to reach the most appropriate decision in terms of relay probability.

In terms of the output, each fuzzy system produces a cost. The costs $w_1(ij)$ and $w_2(ij)$ are respectively derived based on relay probabilities $RP_1(ij)$ and $RP_2(ij)$ determined by the defuzzification process, precisely $w_k(ij) = \frac{1}{RP_k(ij)}$ and $k = 1, 2$. The two costs from both fuzzy systems will then be merged together into the total link cost w_{ij} for link ij which will eventually be used for shortest path calculation.

The fuzzy rule base defined in our design consists of 5 rules for FS1 and $5^2 = 25$ rules for FS2. Tables I and II show the IF-THEN rules used in the proposed fuzzy systems FS1 and FS2, respectively. As can be seen from the tables, human logics are involved in the design. For example in FS1 rule base, IF $RE(i)$ is very low THEN $RP_1(ij)$ is very low, since low residual energy should be avoided, hence low relay probability should be assigned leading to high cost.

When new crisp inputs arrive into the fuzzy systems, they are fuzzified to linguistic values and the correspondent rules are triggered. All the rules are processed in parallel by a fuzzy inference engine. We have employed the most commonly used fuzzy inference technique, called the Mamdani method, because of its simplicity. Any rule that fires contributes to the final fuzzy solution space. After aggregating the results obtained from each rule, a defuzzification method is used to calculate the final crisp output value from the fuzzy solution space. This value represents the relay probability for the link ij. The higher the relay probability, the lower the cost, and the more appropriate the link for data forwarding.

Our fuzzy systems use the Centroid technique for defuzzification. This technique determines the balance point of the solution fuzzy region where a vertical line divides the combined set into two equal parts. This method is sensitive to all the rules and it involves simple computation that is suitable for the resource constrained WSN nodes. Mathematically, the Centroid method can be described by the following equation:

$$RP = \frac{\sum_{i=1}^{n} V_i U_A(V_i)}{\sum_{i=1}^{n} U_A(V_i)}, \tag{7}$$

where RP is the relay probability, A is the solution fuzzy region, V_i is the centre of the output fuzzy set corresponding to rule i, n is the number of rules triggered in the fuzzy inference engine and $U_A(V_i)$ is the membership degree for the corresponding output fuzzy set.

In the following, we discuss the computational complexity of DEFL in comparison to the other algorithms evaluated in our work such as MTE, MDR and FA. The complexity of DEFL compromises two aspects: individual link costs produced by fuzzy mapping systems (i.e. Cost 1 and Cost 2) and the final link cost. The time complexity of fuzzy operations is $O(1)$ [22] for a single link cost calculation. Hence, time complexity of each of Cost 1 and Cost 2 calculations for a node is $O(n)$ where n is the number of neighboring nodes. The next step in DEFL is to calculate the final link cost for all links connected to a node which also results in $O(n)$ complexity. Accordingly, the time complexity of DEFL is $O(n)$ which is linear and depends on the number of neighbors. Meanwhile, all other evaluated algorithms calculate the final link cost directly using the crisp inputs and have the same time complexity of $O(n)$.

DEFL requires additional memory capacity for storing the fuzzy mapping functions and the fuzzy rules. However, since this requirement is fixed, i.e. it uses a constant amount of memory regardless of the size of network and number of neighbors, the complexity is $O(1)$. On the other hand, all evaluated algorithms including DEFL consume memory for the data collected from the neighbor nodes which depends on the number of inputs collected and the number of neighbors. Therefore, computational complexity in terms of memory is again linear, i.e. $O(n)$.

Table II: Fuzzy rules for FS2.

No.	Transmission Energy (TE)	Drain Rate (DR)	Relay Probability (RP_2)
1	Very Low	Very Low	Very High
2	Very Low	Low	Very High
3	Very Low	Medium	Very High
4	Very Low	High	High
5	Very Low	Very High	High
6	Low	Very Low	High
7	Low	Low	High
8	Low	Medium	High
9	Low	High	Medium
10	Low	Very High	Medium
11	Medium	Very Low	Medium
12	Medium	Low	Medium
13	Medium	Medium	Medium
14	Medium	High	Medium
15	Medium	Very High	Medium
16	High	Very Low	Medium
17	High	Low	Medium
18	High	Medium	Low
19	High	High	Low
20	High	Very High	Low
21	Very High	Very Low	Low
22	Very High	Low	Low
23	Very High	Medium	Very Low
24	Very High	High	Very Low
25	Very High	Very High	Very Low

VII. Performance Evaluation

In this section, the performance of our proposed algorithm (DEFL) is evaluated in terms of network lifetime, energy efficiency and energy consumption balancing properties, for different traffic load conditions. A comparison is performed between DEFL and its closest peers, including minimum total energy (MTE), minimum drain rate (MDR) and flow augmentation (FA).

MTE and FA are used in our comparison due to their superior performance in terms of energy efficiency and energy balancing, respectively. Both algorithms are popular and have been recently used for comparison in similar works, such as in [3] and [4]. MDR is used in our comparison because, similar to DEFL, it considers traffic load conditions and energy consumption rate which enables this algorithm to perform well in uneven traffic load situations.

A. Simulation Setup and Assumptions

As in the existing works [19], [6] and [17], we carry out our simulation using Matlab. We follow the assumptions and system parameters used in [6] in all our experiments, which are:

1) We assume that residual energy levels, energy consumption rates and sink access cost values of neighbouring nodes are updated and the shortest path computation is completed within the routing update period σ.
2) To focus on the energy consumed in data communications, we omit the energy consumed in the communication of routing control packets and in the computation of the shortest path and fuzzy system outputs.
3) Similar to [6], we use routing update period of $\sigma = 5000$ bits which is equivalent to having routing updates every ten packets of size 500 bits. As discussed in [6], the larger the routing update period σ, the less frequent the required updates which reduces the routing overhead at the cost of deteriorated performance. Whereas, the smaller the update period, the more frequent the routing updates and the better the performance.
4) A commonly used model for the energy dissipation of radio hardware is assumed (similar to [6]). The model is explained in Section IV-C.

Two different network topologies are used in our simulation. In both networks, we assume that heterogeneous sensor nodes are deployed with different initial battery capacity E_i, while the sink node is assumed to have unlimited energy resources. Additionally, the nodes generate traffic at different rates.

1) Network A: A simple network of 10 nodes is created to clarify the concept. The nodes are distributed in an area 40 m by 40 m, as shown in Fig. 4. There is a single sink node (node 1) located at (33, 20) and 9 sensing nodes, each node has a transmission range of 20 m. Nodes 5 and 6 are equipped with a greater initial battery capacity of $E_i = 8J$, and all other sensing nodes have initial battery capacity of $E_i = 1J$. The traffic rate, TR, generated at these two nodes varies between 2 and 22 packets/sec in different experiments, while other nodes generate an average of one packet/sec.
2) Network B: We adopt the same network topology used in [6], mainly to ensure fair comparison with FA which operates using its optimal parameter of $x = 30$ for this network. The network consists of 20 nodes distributed

in an area of 50 m by 50 m, as shown in Fig. 5[1]. There is one sink node (node 20) and 19 sensing nodes, each node has a transmission range of 25 m. Nodes 1 and 10 are equipped with initial energy of $E_i = 80J$ and all other sensing nodes have initial energy of $E_i = 10J$. The traffic rate generated at these two nodes varies in different experiments, while other nodes generate an average of one packet/sec or $TR = 1$.

A summary of the simulation parameters described above is listed in Table III.

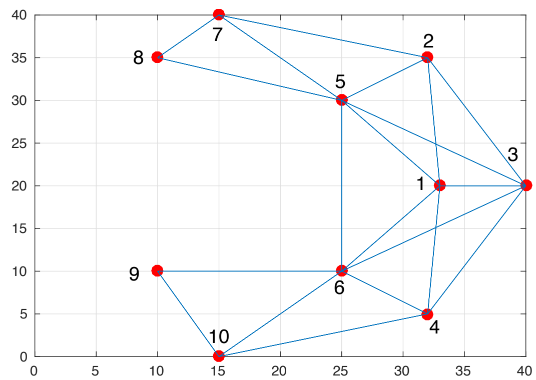

Fig. 4: Network A.

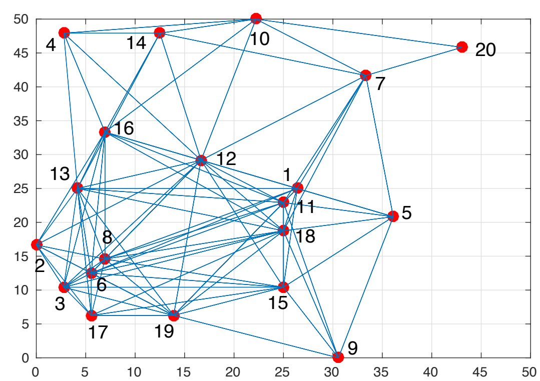

Fig. 5: Network B.

B. Setting τ Parameter

In our design, we use equation (6) to aggregate the two costs from the two fuzzy systems and produce the final link cost. Different weights are assigned when aggregating the two costs. Here we explain the mechanism of assigning the appropriate weight factor τ.

At the start of network operation, all nodes have large amount of energy and hence the route should be selected based on the energy consumption rate related cost. As the residual energy of nodes decreases, it is more important to pay attention to the residual energy related cost, particularly avoiding nodes with low residual energy for forwarding.

[1]This network topology follows the example network illustrated in Figs. 8 and 9 in [6]. The coordinates of each node starting from node 1 are given as follows: (26.389, 25), (0 ,16.667), (2.778, 10.417), (2.778, 47.92), (35.50, 20.83), (5.556, 12.5), (33.33, 41.608), (6.944, 14.58), (30.556, 0), (22.22, 50), (25, 22.917), (16.667, 29.167), (4.1667, 25), (12.5, 47.92), (25, 10.417), (6.944, 33.33), ... (5.556, 6.25), (25, 18.75), (13.889, 6.25), (42.095, 45.833)

Table III: Simulation Parameters.

Parameter	Value
Topological area	Network A: 40 m x 40 m, Network B: 50 m x 50 m
Number of nodes	Network A: 10, Network B: 20
Transmission range	Network A: 20 m, Network B: 25 m
Data packet size	500 bits
Routing update period	5000 bits (10 packets)
Energy consumed at the transmitter amplifier	$100pJ/bit/m^4$
Energy dissipated in transmitting circuitry	50 nJ/bit
Energy dissipated in receiving circuitry	150 nJ/bit

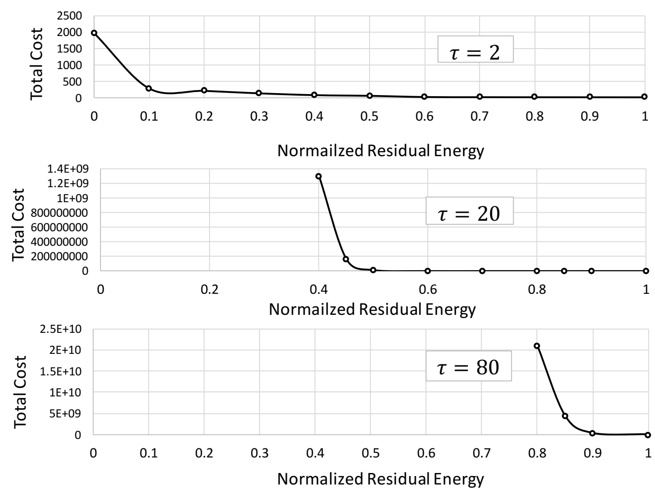

Fig. 6: The total link cost for τ = 2, 20 and 80.

Fig. 6 shows the total link cost $w(ij)$ plotted against normalized residual energy for $\tau = 2, 20$ and 80. These plots demonstrate how the link cost is impacted by the choice of τ. The value of the normalized residual energy (i.e. fraction of the initial battery energy) at which the cost curve takes a sharp rise indicates the turning point at which the link cost becomes high and hence less desirable for forwarding. We see that different τ values create different turning points. When setting $\tau = 80$, the link becomes undesirable for forwarding when the normalized residual energy of the node is still as high as 90%. This means that the link will not be used and the effect of other metrics will be simply omitted so early in the network operation. On the other hand, when setting $\tau = 2$, the link becomes undesirable for forwarding only when the normalized residual energy of the node is below 10%. This late turning point causes the node to be selected excessively which delays the strategy of avoiding low energy nodes and hence leaves no sufficient time to prevent the early expiry of network lifetime. We observe that there is a range of settings for τ to achieve an appropriate turning point. Our experiments show that setting $\tau = 20$ gives a turning point at 50% of the normalized residual energy. This turning point allows the node to be sufficiently utilized until when its energy level becomes reasonably low.

In Fig. 7, we further show the lifetime performance for

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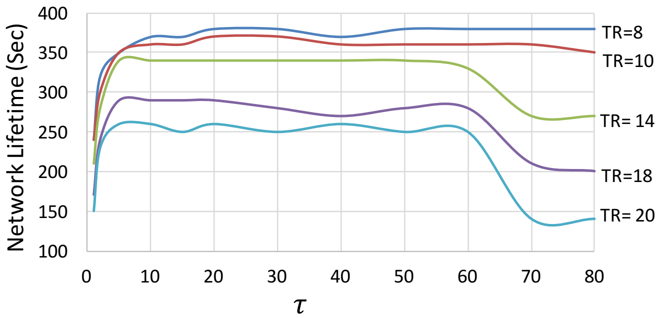

Fig. 7: Network lifetime versus τ, for different traffic rates.

different traffic load configuration, across a range of τ values. As can be seen from the figure, the performance remains relatively constant for a wide range of τ values. This indicates that the precise setting of τ within this wide range is not critical to achieve the best performance. However, we should note that this appropriate range of τ is dependant on network topology and configuration.

C. Network Lifetime Performance

In this subsection, the network lifetime obtained by using DEFL algorithm is compared with the optimal network lifetime computed by the solver, and the lifetime of other existing algorithms including MTE, MDR and FA. Simulation results are presented for both networks, Networks A and B, at different traffic load conditions.

Fig. 8 and Fig. 9 show network lifetime in seconds for Network A and Network B, respectively. As defined earlier, the end of network lifetime is triggered by first-node-dies (FND) event.

Both figures clearly demonstrate that our proposed algorithm outperforms MTE, MDR and FA algorithms at different traffic load conditions. DEFL algorithm constantly shows performance very close to the optimal lifetime reported by the solver. The x-axis shows traffic rates of specific nodes in the network. When the rates of these nodes are low, traffic load is relatively even among all nodes. As the rates of these nodes increase, they generate considerably higher traffic load than other nodes and hence consume more energy. In this uneven load condition, these nodes are critical for the network lifetime.

MTE uses the shortest path method based on transmission energy metric. Without considering residual energy of the nodes, MTE always chooses the minimum energy routes which depletes the energy of the nodes on these routes much faster than other nodes and shortens the network lifetime. Since MTE route selection is not affected by the traffic load conditions, its network lifetime performance remains constant regardless of the traffic rate variation. However, as the traffic loads of specific nodes become sufficiently high, these nodes become critical and they limit the network lifetime.

FA uses both transmission energy and residual energy metrics to compute the shortest path. Since FA emphasizes the residual energy metric in the cost function design, it tends to utilize nodes with higher energy level. In general, this contributes to reasonably good network lifetime performance of FA. However, in cases where these nodes also generate high traffic load, they should be avoided for data forwarding. Since FA does not consider any traffic load related metric, it will continue to utilize these nodes for forwarding regardless of their high drain rate. This misjudgement in FA operation causes fast energy depletion in these nodes and shortens the network lifetime. As can be seen from Figs. 8 and 9, FA performs poorly under uneven load scenarios which indicates its lack of adaptability to variable traffic conditions.

MDR uses both residual energy and energy drain rate of nodes to compute the shortest path. MDR captures traffic load conditions via energy drain rate metric and consequently copes well when traffic loads vary among different nodes. However, the cost function design conservatively combines the two metrics which leads to underperformance in some situations. As can be seen in Figs. 8 and 9, MDR gives lower performance compared with other algorithms when traffic load is distributed more evenly among different nodes.

We see that while an algorithm performs well in certain conditions, it underperforms in other conditions. As explained earlier, emphasizing an inappropriate metric in a particular network condition can lead to significant performance issues. This is the main reason why the existing algorithms fail to perform consistently well under all network conditions. However, our proposed algorithm based on fuzzy logic design avoids rigid computation that can cause inappropriate emphasis of metrics. As shown in Figs. 8 and 9, DEFL algorithm maintains high performance in all traffic load conditions. The performance of DEFL exceeds the best of all tested algorithms under all network conditions. In addition, it achieves network lifetime performance very close to the optimal lifetime obtained by the solver.

A set of random networks are generated to test the performance of the proposed algorithm. For each network, the nodes with high battery capacity are randomly selected to further study the effect of the location of these nodes. It has been observed that the algorithm performance is consistent throughout all the tested random configurations. Using an example of a typical random network of 20 nodes randomly distributed in an area of 50m by 50m[2], the network lifetime performance is evaluated for different random locations of high battery nodes. The average lifetime under different traffic rates is presented in Fig. 10.

D. Energy Consumption Performance

The energy efficiency of a routing protocol is one of the key indicators of its network lifetime performance. A routing protocol should always efficiently consume energy for data forwarding while maintaining a long network lifetime. In this subsection, we investigate the energy consumption properties of the evaluated protocols.

In Figs. 11 and 12, we plot the average energy dissipated per second for Networks A and B, respectively. It is calculated by

[2]The sink node is located at (50,50) and the transmission range is set to 25m for all nodes. All nodes have initial battery capacity of 10J except for two nodes which are configured with 80J battery capacity and their location is randomly selected in each experiment.

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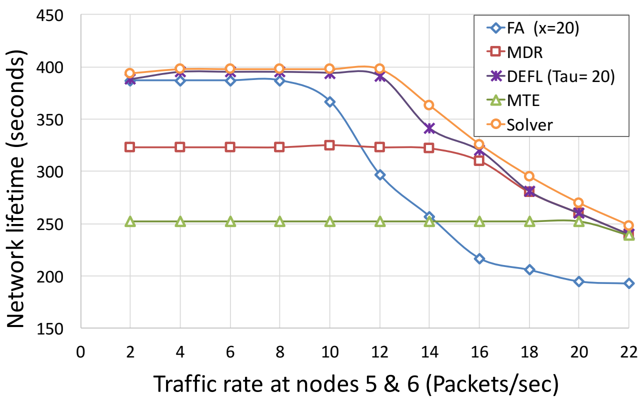

Fig. 8: Network lifetime performance of different algorithms (Network A).

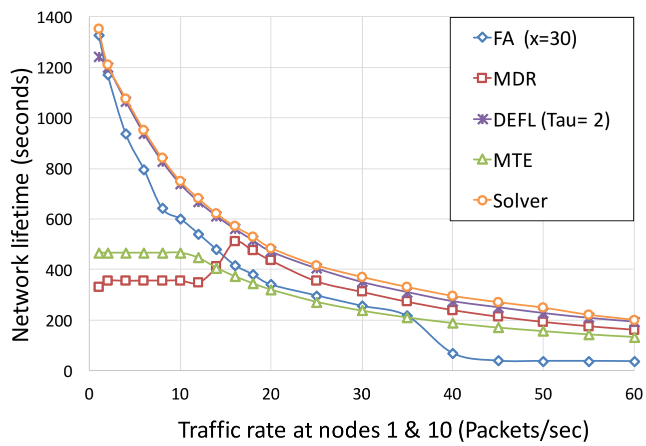

Fig. 9: Network lifetime performance of different algorithms (Network B).

dividing the total energy dissipated by all nodes in the network (in Joules) by the network lifetime (in seconds). As can be seen, the energy efficiency performance of MTE is better than all other protocols in both network topologies. Since MTE only considers minimizing transmission energy, it naturally performs well in this aspect. However, this alone does not guarantee good performance in terms of network lifetime. As reported in Figs. 8 and 9, MTE has poor network lifetime performance. To improve the network lifetime performance of any routing algorithm, energy efficiency should inevitably be compromised to achieve a better energy consumption balancing property. As shown in Figs. 11 and 12, FA, MDR and DEFL have higher energy consumption than that of MTE.

In Fig. 11 , due to the limited number of hops in Network A and the very similar distance of different routes (from each source node to the sink), the energy consumption of using different routes is very similar. Hence, while MDR, FA and DEFL are trying to ensure energy balancing they are not making a huge compromise in terms of energy efficiency since the alternative routes are limited and they all consume similar amount of energy. Therefore, all the algorithms perform very similar in terms of energy efficiency. Meanwhile, for Network B, we can see from Fig. 12 that the availability of many alternative routes which greatly vary in terms of their

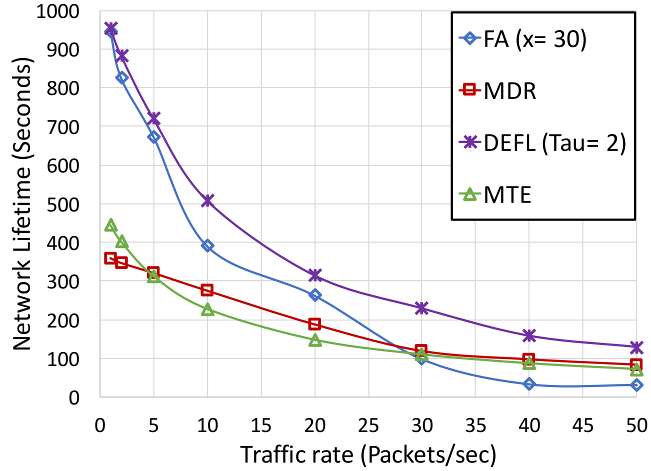

Fig. 10: Average network lifetime performance of different algorithms for a random network with different random configurations.

energy consumption, results in greater variation in the energy efficiency of different algorithms.

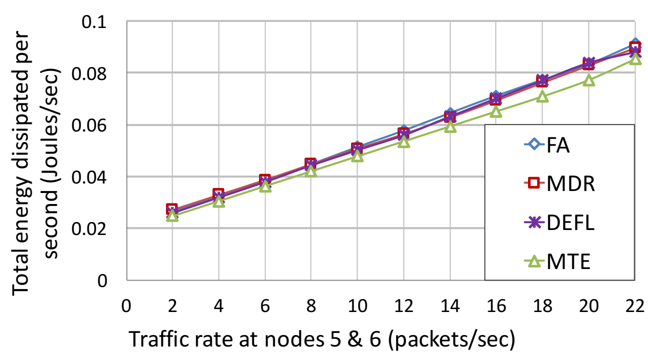

Fig. 11: Average energy consumption rate of different algorithms (Network A).

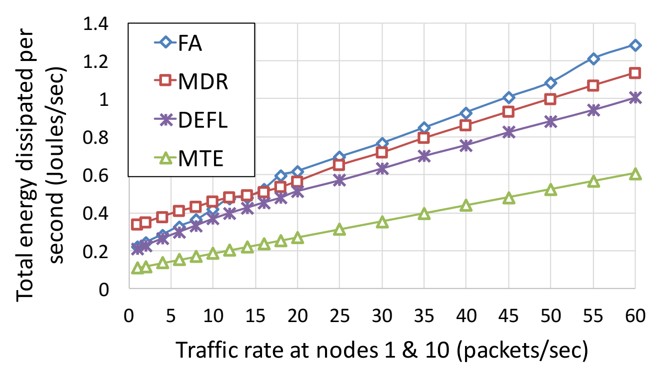

Fig. 12: Average energy consumption rate of different algorithms (Network B).

E. Energy Balancing Performance

As discussed in the previous subsection, while energy efficiency should be as high as possible, it is necessary to compromise energy efficiency to obtain longer network

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lifetime. Reduction in energy efficiency should translate into more balanced use of energy which in turns improves network lifetime. We shall investigate the energy balancing properties in the following.

In Figs. 13 and 14, we show the distribution of residual energy of all sensing nodes at the end of the network lifetime for Network A, with two cases of traffic rate $TR = 6$ packets/sec and $TR = 18$ packets/sec respectively. A distribution with lower average residual energy indicates a more balanced use of energy. As we can see, DEFL algorithm always gives the lowest average residual energy. In particular, in Fig. 14, using our proposed protocol, 89% of the nodes have normalized residual energy of less than 0.13 at the end of network lifetime. Whereas for other protocols, there are more nodes with high residual energy when first node depletes its battery. The next best is MDR, where 78% of the nodes have residual energy less than 0.14 at the end of network lifetime. FA ranks third, while MTE has the worst energy balancing performance.

The two figures demonstrate the poor energy balancing feature of MTE algorithm which in turn explains its poor network lifetime performance. On the other hand, while FA algorithm shows good energy balancing capability at low traffic rates $TR = 6$, this capability deteriorates when nodes 5 and 6 generate higher traffic rate $TR = 18$. For MDR the opposite is observed; at high traffic rates the protocol exhibits good energy balancing performance, however, at low rates its energy balancing performance is generally poor. Meanwhile, all results demonstrate the superior energy balancing feature that our proposed protocol holds.

Similarly, we use two cases of traffic load $TR = 8$ packets/sec and $TR = 40$ packets/sec for Network B and plot the residual energy distribution in Fig. 15 and Fig. 16, respectively. We observe the same behaviour as that in Network A.

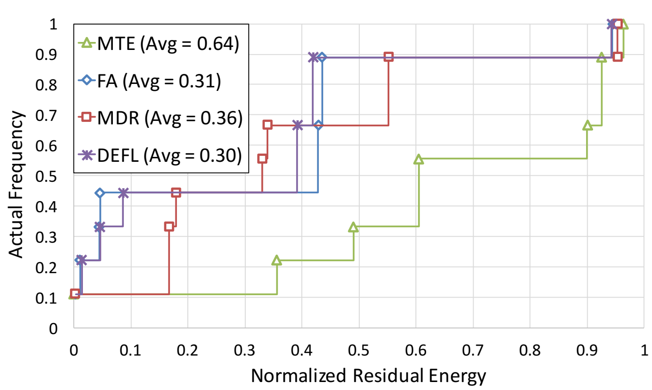

Fig. 13: Residual energy cumulative distribution for different algorithms at TR= 6 packets/sec (Network A).

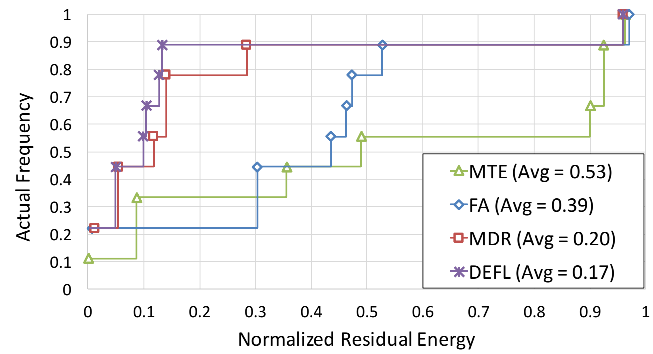

Fig. 14: Residual energy cumulative distribution for different algorithms at TR= 18 packets/sec (Network A).

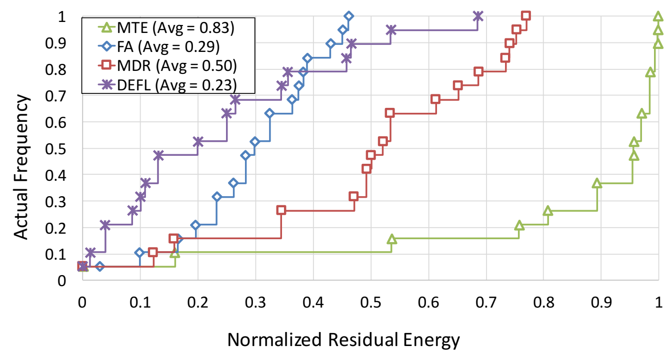

Fig. 15: Residual energy cumulative distribution for different algorithms at TR= 8 packets/sec (Network B).

VIII. Conclusion

In most WSN deployments, extending network lifetime is the main design objective of routing protocols. To achieve this objective, energy-aware routing protocols should be designed to make an appropriate trade-off between energy efficiency and energy consumption balancing among the sensor nodes. Existing works have assumed homogeneous nodes with uniform traffic distribution in their proposed algorithms, hence they fail to perform well in heterogeneous networks with uneven traffic distribution assumed in this work. Additionally, cost function based routing algorithms are widely adopted due to their distributed implementation. However, the proposed cost functions are often based on arbitrary design and lack soft human logic in their calculation. In this work, we formulate the maximum lifetime routing problem and use it to obtain the upper bound network lifetime of a given network configuration. Moreover, we provide a generic framework for the design of energy-related cost functions and utilize fuzzy logic mapping to blend different metrics and achieve superior performance under different network conditions. The simulation results demonstrate the performance improvements obtained by our algorithm (DEFL) when compared to other conventional algorithms such as FA, MTE and MDR. The proposed algorithm has several desirable features. First, it is distributed and hence supports scalability. Second, it successfully trades off energy efficiency for improved energy balancing performance. Third, DEFL is adaptive to network conditions. Last, it provides flexible system design by using easily tune-able fuzzy rules. As future work, we plan to consider delay constrained WSN applications and design a routing protocol that can achieve the best trade-off between maximizing network lifetime and minimizing end-to-end delay in multi-hop networks.

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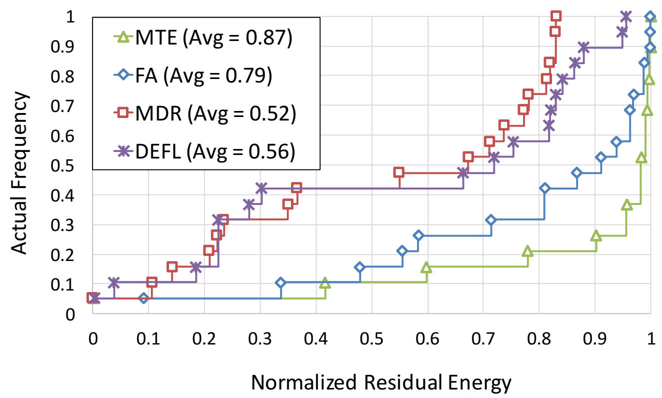

Fig. 16: Residual energy cumulative distribution for different algorithms at TR= 40 packets/sec (Network B).

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This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TGCN.2018.2799868, IEEE Transactions on Green Communications and Networking

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