Fuzzy-based Routing Metrics Combination for RPL

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1 INTRODUCTION

The routing protocol is a key functionality of any communication network, it must support effective transport of data from one point to another in the network. Due to the many opportunities that they offer, these recent years, Wireless Sensor Networks (WSN) are the subject of a growing interest for industrial and scientific communities. Such environment must face with severe constraints, such as fragile nodes with low energy capabilities, low data rate over a sharing medium with unstable and lossy transmission links. WSN protocol designers must take into account many parameters and challenges different from those of traditional wired networks.

It is in this context that the Internet Engineering Task Force `roll` working group was chartered a few years ago, to design a routing protocol for Low-Power and Lossy Network (Winter et al., 2012). Very recently, the later has started to provide their results: the IPv6 Routing Protocol for Low-Power and Lossy Network (RPL) and other companion documents. The protocol was designed with the purpose of separating the packet processing and forwarding from the routing optimization goal. A number of metrics (Vasseur et al., 2012) are intended to be included by the protocol during the network topology building phase, implemented as an objective function. So far, only two objective functions are specified: one using the hop-count as routing metric also called `of0` (Thubert, 2012), the other making use of the expected number of transmission needed to successfully send a packet to its destination (ETX) namely `Minimum Rank with Hysteresis Objective Function` (Gnawali and Levis, 2012). Use of other defined criteria are left to implementer, also the possibility of combining several metrics into one, to ensure quality of service or meet application requirements, is not well-addressed.

This problem, including for RPL protocol has already been investigated in the literature (Karkazis et al., 2012), and falls into two forms of combination: additive and lexicographic. In this paper we propose to take advantage of fuzzy logic to solve it. This approach is motivates by the fact that, using this paradigm, with a small memory footprint, we can seek for a halfway between several criteria, even antagonistic. Contrary, with the two aforementioned method, metrics must follow the same direction (growing or decreasing).

The remainder of the paper is organized as follows. Section 2 presents related works on combining metrics for routing in WSN, as well as works that use fuzzy inference system for routing design. Section 3 describes an overview of RPL protocol. In section 4, we detail the proposed objective function design, followed by implementation parameters, experiment results and discussions in section 5. Finally, we conclude and discusses future directions in section 6.

2 RELATED WORK

The diversity of applications that WSN are called to support imposes different requirements on the underlying network with respect to delay, loss and energy criteria. That is why (Karkazis et al., 2012) propose to use additive and lexicographic composition to optimize more than one performance aspect. In the additive approach, the composite metric is written as a linear combination of basic metrics ($M = \sum_i \alpha_i m_i$). The main shortcoming of this scheme is that the basis metrics must necessarily be defined on the same order relation, thereby restricting the type of metrics to be considered. The lexicographic approach overcomes this, but its drawback is that basic metrics are evaluated sequentially, the next is taken into account only to break the tie. So that, some metrics are frequently not take into consideration.

For instance, Link Estimation and Parent Selection protocol (Yan and Sun, 2007) uses hop-count and Link Quality Indicator (LQI) in lexicographic manner to select the next hop. The source node selects the neighbouring node which has the minimum hop to the sink node as its next hop node. If there is more

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than one node having the minimum hops, the one which has the largest LQI is chosen. The main disadvantage of this protocol is the early death of nodes and the unbalanced energy dissipation. To overcome this, RPLRE (Yan et al., 2009) based as the previous on LQI and hop-count, suggests to take into account probability selection and additionally residual energy when choosing next hop node. This improves the latter by avoiding to select the same node more often. The result is a more balanced energy consumption among potential parent of a given node, and the network lifetime is thereby extended.

(Aslam et al., 2004) propose a composite metric that uses multiple parameters to find optimal route, given the QoS constraints for Optimized Link State Routing (OLSR) protocol. This routing is natively based on hop-count. The objective of this composite metric is to find an optimal path with maximum available bandwidth and minimum delay and jitter. The latter is computed as a linear combination of the given parameters.

In (Heo et al., 2009), authors proposed EARQ, a novel routing protocol for wireless industrial sensor networks. The protocol provides real-time, reliable delivery of a packet while considering energy awareness. The path with the lower energy cost is selected according to a probabilistic model, in addition only paths that may deliver packets in time are selected to achieve real-time requirement. Source node may send a redundant packet via alternate path if the reliability is not meet. Contrary to previous methods, EARQ consider these three criteria (energy, latency and reliability) separately, instead of a single combined metric. Moreover, protocol supposes that every node knows it location and rely on a GPS mechanism or location process for that, but this not always the case for many WSN deployment.

There are many growing interest of integration of artificial intelligence technologies like fuzzy rule-based systems to design protocols for WSN. GAFO (Ghataoura et al., 2009) uses a genetic adaptive fuzzy hop selection scheme, to make optimal choices for robust packet transmission in WSN involved in varying channel conditions. The paper describes a fuzzy system engine that takes signal to noise ratio and outage probability as input, to determine the possibility of a neighbour node to be selected as the next hop for data forwarding. Experiments show that in the same conditions, this protocol outperforms the crisp approach on average by 20% for reliability and 15% for total energy consumption.

A cluster head election method using fuzzy logic has been introduced by (Gupta et al., 2005) to overcome the defect of LEACH (Heinzelman et al., 2000), a popular cluster head selection technique. The main idea of LEACH protocol is that node are elected depending on a stochastic model and uses localized clustering. The consequence is that some cluster heads may be very close to each other or may be located in the edge of the WSN. This careless cluster heads distribution could not maximize energy efficiency. Other schemes (Basirnezhad and Torshiz, 2011; Ran et al., 2010) were proposed to improve election process involved on LEACH. Those have proved that the network lifetime can be efficiently prolonged using fuzzy variables (concentration, energy and node centrality). Unfortunately, LEACH is not applicable to networks deployed in large regions, since it uses single-hop routing where node can transmit data directly to cluster head, afterwards the latter transmit data to the sink.

EDARP (Zeynali et al., 2009) is another work targeting the routing plane. Contrary to LEACH were each cluster head directly sends data to sink, protocol establishes a *Fuzzy Spanning Tree* that uses the energy and distance to construct a routing path over all cluster heads. These two criteria is used to generate a *fuzzy election number* and lead to the selection of the best parent into the routing tree. EDARP balance energy consumption among all nodes by keeping rotation in cluster head election, and parent's node selection in whole lifespan of the network.

Unlike the previous protocols that uses a clustering mechanism to build a hierarchical topology, FEAR (Almomani and Saadeh, 2011), directly build a logical tree topology between network nodes. They aim to enhance the existing tree-based routing in terms of reducing the number of hops and solving the problem of node/link failure. The protocol uses a ranking system based on fuzzy inference so that nodes rank their neighbours considering both neighbours depth and power. The fuzzy ranking system is used to construct and maintain the tree topology. Compared to RPL, FEAR generates more control messages which implies a greater power consumption, since communication operations are the more power consumer. In addition, the protocol uses a node identification (ID) construction model where a node's ID is computed based on the node's parent ID. Thus when a parent node dead, all nodes in its subtree must recomputed their ID as soon as a new parent is found, involving more processing and communication operations.

3 RPL OVERVIEW

RPL (Winter et al., 2012) is a distance vector routing protocol optimized for low power and lossy network where multipoint-to-point is the dominant traffic pattern. The protocol also support point-to-multipoint traffic pattern using destination advertisement mechanism, and provide a basic structure for point-to-point route. The network topology is organized as one or more Destination Oriented Direct Acyclic Graph (DODAG) each rooted at a single point, that act as sinks for the topology. Three new types of ICMP messages are defined and manipulated:

- DODAG Information Object (DIO) used to create and maintain upwards routes.
- DODAG Destination Advertisement Object (DAO) used to install downwards routes.
- DODAG Information Solicitation (DIS) actively used by a node wishing to join the network or asking for more recent informations.

The topology building starts at the root (initially, the only router which is part of a DODAG), that sends DIO messages in its neighbourhood. This message contains all common configuration parameters, including root ID, mode of operation, timers values, etc. Upon receipt of a number of such messages, neighbour nodes may participate in the DODAG according to the objective function (OF), select theirs parents and then start emitting their own DIO messages. This process spreads gradually to cover the whole network as new nodes join the DODAG. Only one node among parent's nodes (*the preferred parent*) acts as the next-hop on the path towards the root.

RPL pro-actively creates and maintains the topology, by regularly sending ICMP control messages in the vicinity. The frequency of these exchanges are governed by the trickle algorithm (Levis et al., 2011), that reduce the overhead induced by control messages. This is done by sending DIO less often when the topology is steady, but reacts and propagates rapidly informations on topology change or when inconsistencies are detected.

An important point is when a node received more than one *consistent* DIO, each from a different neighbour and must choose which is the preferred parent. This choice is governed by the objective function that specifies how the node selects the best parent into the parent set, and calculates its own rank (the relative position with respect to the root) from the parent's rank. Different criteria also called routing metrics are defined (Vasseur et al., 2012) to capture link or node characteristics on the path for parent selection. The rank calculation is derived from the set of these selected metrics, and must monotonically decrease as we move toward the root. This last property enables the routing structure to maintain its acyclic nature and helps to avoid routing loops.

Unlike existing OFs (Gnawali and Levis, 2012; Thubert, 2012) that use only one metric to construct the DODAG, we want to integrate QoS into RPL by taking into account more than one performance aspect. The next section shows how we design such OF using fuzzy inference system.

4 ROUTING METRIC DESIGN

4.1 Fuzzy Inference System

Fuzzy logic reasoning allows us to transform several input variables (delay, ETX and energy) into one (Quality). The fuzzy inference system consists on several steps.

- Fuzzification: take a crisp value input and determine its degree of membership (fuzziness) for the appropriate fuzzy sets.
- Fuzzy inference: Apply combination rules to fuzzified inputs and compute a fuzzy output.
- Aggregation: If an output depends on more than one rule, this step unifies all values into one.
- Defuzzification: Convert the fuzzy output obtained at the previous step into a crisp value.

In this paper, due to its simplicity and efficiency, we use the most common fuzzy inference method named Mamdani model (Mamdani, 1977).

4.2 Composite Metric Design

In order to illustrate the mechanism of fuzzy logic composition, we consider the network topology depicted in the figure 1. Node N, in order to send data to the destination S, must select the next hop (between P1 and P2) as parent. This choice is governed by received informations as shown, according to the fuzzy inference engine.

4.2.1 Linguistic Variables

Node's performances knowledge are represented as linguistic variables:

- ETX - The expected number of required transmissions before a packet reaches the destination.
- Delay - The average time for a packet to reach its destination.

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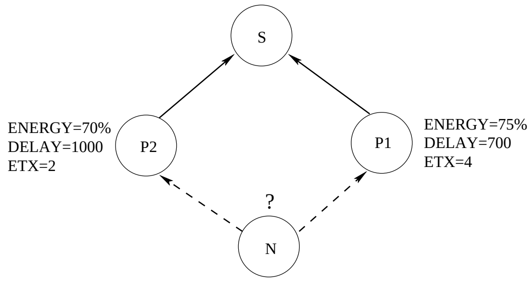

Figure 1: Parent Selection Process.

- Energy - The energy cost of the path, also energy of the node having the smallest remaining battery level on the path.

We use cross-layer mechanisms to retrieve ETX and delay from data link and network layers. Node's energy is estimated based on the real-time energy estimation model described by (Rahmé and Fourthy, 2010) and implemented by (Nataf and Festor, 2013).

4.2.2 Fuzzification Process

To avoid the complexity of combining directly three variables into one, we perform the fuzzification process in two stages, as shown in the figure 2.

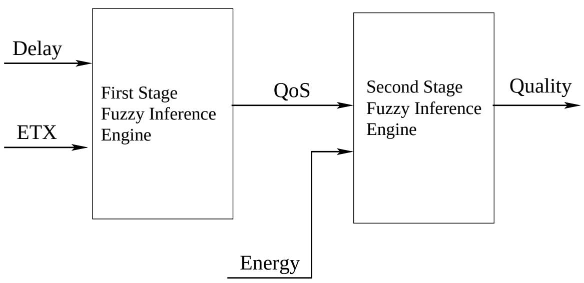

Figure 2: Fuzzy Inference Engine.

First Stage Fuzzification

On the first stage, we combine delay and ETX as input to compute QoS which is taken in its turn as input for the next stage. The linguistic variables used to represent delay are divided into `small, average` and `high` membership functions, and ETX fall into `short, average` and `long`. Figure 3 depicts their membership functions parameterized by the number of hops (*hc*) upwards to the sink, as delays (respectively ETX) are comparable only at the same hop count.

Table 1 illustrates the relationship between these two linguistic variables for the computation of QoS. So, short is the ETX and small is the delay, better is the QoS to consider.

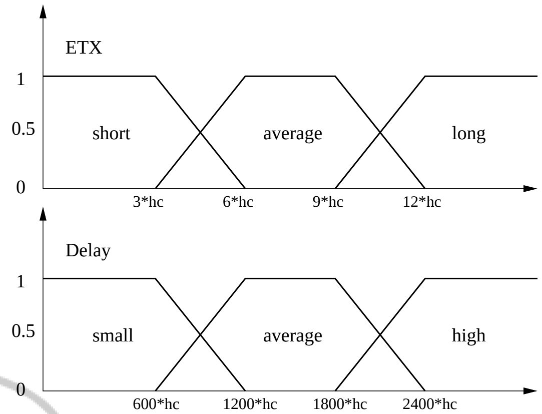

Figure 3: Membership functions.

Table 1: QoS Output Metric.

ETX / Delay	small	average	high
short	very_fast	fast	average
average	fast	average	slow
long	average	slow	very_slow

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For instance, considering a crisp value ETX, formula 1 indicates how is its the level of membership in the `average` fuzzy set, for one hop (*ie*. $hc = 1$). Similar formulas establish the level of membership for others ETX fuzzy sets, as well as delay and energy linguistic variables.

$$average(etx) = \begin{cases} 0 & \text{if} \quad etx \leq 3 \\ \frac{etx-3}{6-3} & \text{if} \quad 3 < etx < 6 \\ 1 & \text{if} \quad 6 \leq etx \leq 9 \\ \frac{etx-12}{9-12} & \text{if} \quad 9 < etx < 12 \\ 0 & \text{if} \quad etx \geq 12 \end{cases} \tag{1}$$

For the example given in figure 1, node N computes as level of membership `short(etx)=0.66, average(etx)=0.33`, and `long(etx)=0` for the parent node P1. Same types of computations for P1's delay allow us to determine as respective fuzzy sets `small`, `average` and `high`, the values `0.83, 0.16` and `0`.

Since QoS relates to ETX and delay, the previously computed membership functions are combined according to table 1. The Mamdani model allows us to use the *minimum* operator as the composition function, and *maximum* as the aggregation operator. For instance, formula 2 indicates how to compute `average(QoS)` fuzzy set from inputs. In the same way, we establish formulas for fuzzy sets ranging from `very_fast` to `very_slow`.

$$avg(QoS) = \max \begin{pmatrix} \min(long(etx), small(dly)) \\ \min(avg(etx), avg(dly)) \\ \min(short(etx, high(dly)) \end{pmatrix} \tag{2}$$

For the topology in figure 1, node N computes three non-zero QoS membership functions concerning neighbour P1: `very_fast(QoS)=0.66`, `fast(QoS)=0.33`, and `average(QoS)=0.16`. These values are defuzzified (following procedure in §4.2.3) into a single QoS output (`QoS=0.78`), and then used in the next fuzzification stage.

Second Stage Fuzzification

As the second stage of the fuzzy inference system, we combine the previously computed QoS with the energy linguistic variable to provide *Quality*. For a given node, energy could be `low`, `medium` or `full`, and the output values for *Quality* is divided into seven levels ranging from `awful` to `excellent`. Table 2 shows how to derive *Quality* based on QoS and energy.

Table 2: Quality Output Metric.

QoS / Energy	low	medium	full
very_slow	awful	bad	average
slow	bad	degraded	average
average	degraded	average	acceptable
fast	average	acceptable	good
very_fast	average	good	excellent

4.2.3 Defuzzification Process

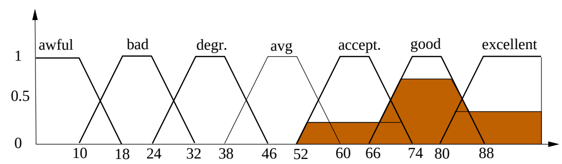

Figure 4: Quality defuzzification.

All fuzzy values obtained after aggregation step are converted into a single crisp output. The most common and accurate defuzzication method uses the centroid, where the result is the center of gravity of the polygon drawn using fuzzy values of the output membership function. Figure 4 illustrates the defuzzification process for *Quality* linguistic variable. Output values range from 0 to 100 and indicate how is the level of quality to choose a neighbour as the next hop, according to the selected metrics.

For the proposed topology, three membership functions are fired as P1 *Quality* output, `accept(Quality)=0.25`, `good(Quality)=0.70`, and `excellent(Quality)=0.30`. The center of gravity for the depicted region is 77. Similar computations produce the value `70` for P2. So, the best next hop for N according to three criteria (ETX, delay and energy) is P1.

5 EXPERIMENTS RESULTS

5.1 Network Model and Assumptions

To evaluate the proposed combined metric, simulations were performed on Cooja (Osterlind and Dunkels, 2006) that emulate real nodes running Contiki OS code. Twenty nodes are randomly scattered in the environment of interest (60×60 m^2 2D-grid) without any isolation. All sensor nodes have the same capabilities, the same transmission range set to 20 *m*, with 30 *m* of interference range, and limited power resources. Sensor nodes, located in fixed places without mobility, sense data and transmit it to the sink for processing at regular time interval. Sink node is assumed to have unconstrained resources. We use as layer 2, ContikiMAC (Dunkels, 2011) that operated on top of IEEE 802.15.4 with non-persistent CSMA and provides power efficiency by nodes keeping their radios turned off for roughly 99% of the time. Table 3 summarizes other setups parameters.

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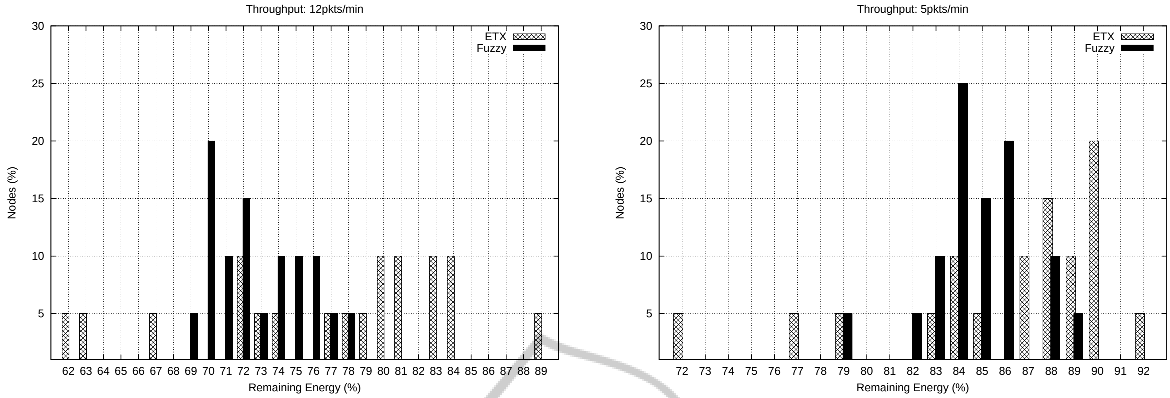
Table 3: Network Setups.

Settings	Value
Wireless channel model	Unit Disk Graph Medium w/ Distance Loss
Communication range	20 *m* (Tx/Rx), 30 *m* (Interf.)
Mote type	Tmote sky
Transport Layer	UDP
Network Layer	μIPv6 + 6LoWPAN
MAC Layer	non-persistent CSMA + ContikiMAC
PHY + Radio Layer	IEEE 802.15.4 w/ CC2420

5.2 Performance Evaluation

We have performed a data collection application. Two scenarios are developed, in the first the RPL routing topology is organized according to the native ETX metric, while the second scenario uses the proposed combined metric according to the fuzzy inference engine. Data are sent to the sink periodically, several tests are launch at various data emission rates, ranging from one to twenty application data packets per minute. Collect application is run for 48 hours, all sensor nodes start with the same battery level. We are interested in the network lifetime by looking at energy depletion of nodes. So the latter is considered as the time on which the first node has completely exhausted its battery (Dietrich and Dressler, 2009). We also estimate the packet reception rate at the sink node, as it measures the transmission accuracy.



(a) (b)

Figure 6: Battery Distribution.

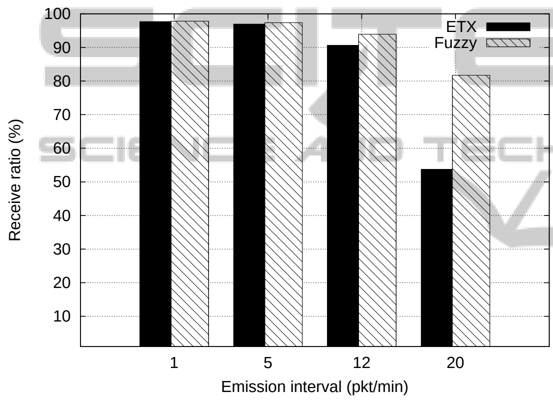


Figure 5: Reception ratio at sink node.

5.2.1 Packet Reception Ratio

Experiments show that for high transmission rates, the combined metric scenario obtain better reception ratio, as depicted by figure 5 at a rate of 12 and 20 packets per minute. When transmission rate is low (one or five packets per minute), both scenarios behave roughly in the same way, although the combined metric scenario obtain slightly better results. This is justified by the fact that, at high transmission rate nodes are faced with more data traffic, thus there is more noise and contention in the network. The combined metric scenario, as ETX scenario, selects nodes with high expected transmission count, but in addition the former favors the least overloaded nodes, since latency takes into account buffer size and contention at the MAC layer. To see this observation in more details, table 4 presents packet loss rates for various emission interval. One can note that, at 20 packets per minute, the single metric scenario loses packets more than twice compared to the combined metric scenario.

Table 4: Packet Loss Ratio.

Scenario / Freq.	1pkt/min	5pkt/min	12pkt/min	20pkt/min
ETX	2.32%	3.05%	9.40%	46.26%
Fuzzy combined	2.20%	2.64%	6.06%	18.29%

5.2.2 Energy Exhaustion

We assess the energy distribution on the network during the routing topology construction. Ideally, we would like to delay as much as possible when the first network node dies, this means for the routing protocol to better balance the energy distribution of nodes (Kamgueu et al., 2013). As shown by the figure 6, at $12 pkts/min$ (fig. 6-a) the combined metric scenario have nodes whose batteries levels range between $69\% - 78\%$, while the same range is $62\% - 89\%$. Furthermore, 15% of nodes in the single metric routing have their remaining power lower than the weakest node in the second scenario. These observations are roughly the same at $5 pkts/min$ (fig. 6-b). The combined metric routing achieved the goal, since node's energy dispersion is lower than the native ETX scenario, also it better delay the first node death. This observation is more accentuated for higher packet emission rates, as nodes exhaust their battery more quickly. This result is not surprising since the combination in addition to others criteria, takes energy into account while the native objective function don't care about that.

6 CONCLUSIONS

In this paper we designed and implemented a new objective function for IPv6 routing protocol for low power and lossy network. The proposed solution aims

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to optimize more than one network performance aspects. We used fuzzy inference system to combined expected transmission count, delay and node's remaining power into one unique value. Experiment results show that the combined metric objective function obtains better results, compared to the ETX scenario, both for network energy distribution and packet reception rates. These results are more highlighted as soon as the data traffic is heavy in the network.

Currently we perform intensive simulations for longer durations, we aim to measure more precisely the influence of latency and jitter on the routing. In our future work, we envision to parameterize the contribution of each metric to fuzzy combination and assess its impacts on the routing. Moreover we plan to implement other forms of metric combinations (namely lexicographic and additive approaches) and compare their simulation results with those obtained with the fuzzy logic.

REFERENCES

Almomani, I. M. and Saadeh, M. K. (2011). Fear: fuzzy-based energy aware routing protocol for wireless sensor networks. *International Journal of Communications, Network and System Sciences*, 4:403–415.

Aslam, N., Phillips, W., and Robertson, W. (2004). Composite metric for quality of service routing in olsr. In *Proc. of Canadian Conference on Electrical and Computer Engineering*, pages 759 – 762, Niagara Falls Ontario, Canada.

Basirnezhad, M. and Torshiz, M. N. (2011). Energy efficient cluster head election using fuzzy logic in wireless sensor networks. *International Journal of Computer Science and Information Security*, 9(5):255–260.

Dietrich, I. and Dressler, F. (2009). On the lifetime of wsn. *ACM: Trans. on Sensor Networks*, 5.

Dunkels, A. (2011). The contikimac radio duty cycling protocol. Technical Report ISBN 1100-3154, SICS.

Ghataoura, D. S., Yang, Y., and Matich, G. (2009). Gafo: genetic adaptive fuzzy hop selection scheme for wireless sensor network. In *Proc. of 5th IEEE International Wireless Communication and Mobile Computing conference (IWCMC)*, Leipzig, Germany.

Gnawali, O. and Levis, P. (2012). The Minimum Rank with Hysteresis Objective Function. RFC 6719 (Proposed Standard).

Gupta, I., Riordan, D., and Sampalli, S. (2005). Cluster-head election using fuzzy logic for wireless sensor networks. In *Proc. of 3rd IEEE Annual Communication Networks and Services Research Conference*, Halifax, Canada.

Heinzelman, W., Chandrakasan, A., and Balakrishnan, H. (2000). Energy-efficient communication protocol for wireless microsensor networks. In *Proc. of 33rd Hawaii International Conference on System Sciences (HICSS)*, pages 3005–3014.

Heo, J., Hong, J., and Cho, Y. (2009). Earq: Energy aware routing for real-time and reliable communication in wireless industrial sensor networks. *IEEE Trans. on Industrial Informatics*, 5(1):3 – 11.

Kamgueu, P., Nataf, E., Djotio, T., and Festor, O. (2013). Energy-based metric for the routing protocol in low-power and lossy network. In *Proc. of 2nd Sensornets*, Barcelona, Spain.

Karkazis, P., Leligou, H. C., Trakadas, P., and Velivassaki, T. H. (2012). Design of primary and composite routing metrics for rpl-compliant wireless sensor networks. In *Proc. of International Conference on Telecommunications and Multimedia (TEMU)*, pages 13 – 18, Chania, Greece.

Levis, P., Clausen, T., Hui, J., Gnawali, O., and Ko, J. (2011). The Trickle Algorithm. RFC 6206 (Proposed Standard).

Mamdani, E. H. (1977). Application of fuzzy logic to approximate reasoning using linguistic synthesis. *IEEE Transaction on Computing*, C-26(12):1182 – 1191.

Nataf, E. and Festor, O. (2013). Online estimation of battery lifetime for wireless sensors network. In *Proc. of 2nd Sensornets*, Barcelona, Spain.

Osterlind, F. and Dunkels, A. (2006). Cross-level sensor network simulation with cooja. In *Proc. of 31st IEEE Conf. SenseApp*, pages 641 – 648, Tampa, Florida.

Rahmé, J. and Fourthy, N. (2010). Energy management for battery-powered embedded systems. In *Proc. of IEEE WCNC*, pages 277 – 324, Sydney.

Ran, G., Zhang, H., and Gong, S. (2010). Improving on leach protocol of wireless sensor networks using fuzzy logic. *Journal of Information & Computational Science*, 7(3):767–775.

Thubert, P. (2012). Objective Function Zero for the Routing Protocol for Low-Power and Lossy Networks (RPL). RFC 6552 (Proposed Standard).

Vasseur, J., Kim, M., Pister, K., Dejean, N., and Barthel, D. (2012). Routing Metrics Used for Path Calculation in Low-Power and Lossy Networks. RFC 6551 (Proposed Standard).

Winter, T., Thubert, P., Brandt, A., Hui, J., Kelsey, R., Levis, P., Pister, K., Struik, R., Vasseur, J., and Alexander, R. (2012). RPL: IPv6 Routing Protocol for Low-Power and Lossy Networks. RFC 6550 (Proposed Standard).

Yan, C., Hu, J., Shen, L., and Song, T. (2009). Rplre: A routing protocol based on lqi and residual energy for wireless sensor networks. In *Proc. of International Conference on Information Science and Engineering (ICISE)*, pages 2714 – 2717, Nanjing, China.

Yan, T. and Sun, L. (2007). Principle and performance evaluation of routing protocol in tinyos. *Trans. on Computer Engineering*, 33(1):112 – 114.

Zeynali, M., Khanli, L. M., and Mollanejad, A. (2009). Edarp : novel energy and distance-aware routing protocol in wireless sensor network. In IEEE, editor, *2nd ICIS : Information Technology, Culture and Human*, Seou, Korea.

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