Fuzzy Diffusion Analysis: Decision Significance and Applicable Scenarios

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Abstract— **Distributed Wireless Sensor Networks (WSNs) operate under severe energy constraints and are largely characterized by short-range multi-hop radio communications, which signify the role of energy-efficient routing schemes for such networks. Fuzzy Diffusion, an energy optimization on the general diffusion schemes for application-aware sensor networks, has been shown to offer substantial improvement in WSN lifetime and connectivity. The initial exploration depicted the advantages of extreme conservative routing in dense WSNs. However, a progressive investigation of fuzzy diffusion is needed to address several important aspects of the protocol mechanism and to quantify its applicability.**

Fuzzy diffusion is primarily based upon energy-aware routing decisions, and so an analysis of the impact of decision-making strategies on the protocol performance is required to substantiate the use of any specific tool. The purpose of this work is to quantify the contribution of fuzzy logic in computing efficient forwarding decisions as compared to simpler, straightforward crisp decision-making strategies. Further, this paper aims at exploring the network and traffic scenarios under which fuzzy diffusion scheme would be efficient, through a series of simulation experiments.

***Index Terms*—Wireless Sensor Networks, Routing, Fuzzy Logic, ns2.**

I. Introduction

Wireless Sensor Networks (WSNs) recently have found extensive application in scientific and military surveillance that often demands continuous and unattended monitoring of physical phenomena for extended periods of time, without the possibility of replenishing the energy supply of nodes. Thus the effectiveness of a WSN depends on its efficiency in using the limited energy supply. Addressing the need for energy efficiency is imperative for any sensor protocol stack.

A typical sensor net comprises several tiny, resource scarce sensors, collaborating in their sensing, processing and communication process to accomplish high-level application tasks. WSNs can be perceived as specialized ad-hoc networks [1] architecturally the same, but with severe resource constraints and unique application demands. Also, for a typical sensor network, short-range multi-hop radio communication provides considerable energy savings as compared to long-range communication [2].

WSNs are generally deployed to achieve a common application task, where information supplied is the prime interest as compared to who sends the information. In that perspective, nodes need not be uniquely identified by network global addresses. A simple local neighborhood identification scheme (low-level addressing [3]) would suffice to diffuse information hop-by-hop to the concerned application entities. In short, sensor networks are characterized by data-centric [4, 5] communication, rather than global node-to-node communication. Accordingly the design considerations for sensor protocols differ from ad-hoc networks, whereby individual node performance metrics (such as per-node throughput or fairness [1]) are insignificant as compared to collective network performance metrics (such as total network energy conserved or total application information delivered).

To address such network characteristics and application demands, several sensor applications rely on data flooding mechanisms to disseminate the required information throughout the network and provide consistent data supply at all regions of the deployed area. Flooding in dense multi-hop networks results in nodes forwarding considerable volumes of packets for other nodes in addition to communicating their own application data. Data-forwarding overhead might become fatal for energy critical nodes, and the residual energy resources at weak nodes largely determine the connectivity and lifespan of a WSN. Fuzzy diffusion [6], a data-centric routing paradigm for application-aware sensor networks, proposed distributed adaptations to alleviate the forwarding burden on energy scarce nodes. This research proceeds with further investigation on the initial scheme.

A. Contributions

The initial results [6] suggested the need for extreme conservative routing in sensor networks to achieve useful energy savings. However, a continual investigation is essential for a complete quantification of the protocol requirements and suitability. In this paper we address two key points left open in the initial investigation of fuzzy diffusion.

1. The influence of decision making strategies on the protocol performance, since the primary protocol logic is based on the energy-efficient routing decisions that filter out redundant network transmissions. We quantify the contribution of fuzzy decision-making by comparing it with a crisp logic alternative (explained in section 3).

2. Performance analysis of fuzzy diffusion under different network and traffic settings to measure its suitability to different applications. The main purpose is to categorize the applications under which fuzzy diffusion would provide useful energy savings, since any data-centric protocol needs to be application matched [5].

B. Related Work

This work builds upon the initial research on fuzzy diffusion for distributed sensor networks [6]. Research in [5] formed the main motivation for quantifying the protocol performance under different application scenarios.

Section II provides a brief review of fuzzy diffusion, followed by a mathematical description of the decision tools analyzed in section III. The implementation details and performance analysis are provided in section IV. Finally, section V concludes with a summary of this investigation.

II. Fuzzy Diffusion Review

This section provides only a conceptual review of the fuzzy diffusion scheme for a basic understanding before presenting the new results. For interested readers, the introductory work in [6] presents a complete description.

A. Fuzzy Diffusion

Fuzzy Diffusion, an energy optimization scheme that embeds with any diffusion [5] algorithm, shifts the energy cost of data forwarding to non-critical nodes, attempting to maintain an energy-balance in the network. Critical nodes (those with low energy reserves and/or heavy application traffic) have reduced data forwarding burden and expend most of their power in sensing and communicating their sensor data, thus seeking to achieve net longevity. The proposed mechanism would be ideal for periodic surveillance applications, where sensors are densely deployed for sustained observation of physical events.

Fuzzy diffusion addressed the challenge of explicitly incorporating the knowledge of relative neighbor energy reserves at the diffusion layer to enable energy-adaptive routing decisions and to reduce the amount of network radio transmissions. By comparison, directed diffusion [4] does not have explicit energy considerations. The initial research was performed with the two-phase-pull [5] variant of the family of diffusion algorithms.

In directed diffusion, nodes forwarding *interests* [4] implicitly agree to forward exploratory data, since it sets up *gradients* [4] that draw data towards the sinks. The positive reinforcement phase of diffusion subsequently enables flow of data at high rate from the source to sink over a single path. The initial interest flooding and gradient set-up costs are huge in diffusion networks; fuzzy diffusion developed optimizations to adaptively reduce these initial costs.

Recognizing that the decision to forward an interest is an offer to expend energy in support of that interest, fuzzy diffusion informed the interest forwarding decision with knowledge of energy reserves at a node and its neighbors. Network nodes *individually decided* whether to forward an received interest or not depending on their network energy status and pending traffic, since re-broadcasting interests implies willingness to be in the data forwarding path from source to sink. The protocol methods created energy awareness in routing such that, at any instant in the network, the load of relaying data is assigned to nodes having relatively plentiful energy reserves, while still maintaining an energy-balance among the nodes. Fuzzy diffusion provides a conservative approach to routing for exploiting the inherent network redundancy.

B. Design

Two factors were used to represent node criticality;

1) Relative Energy Level, $REL = \frac{E_{node} - E_{\min}}{E_{\max} - E_{\min}}$, representing the energy-criticality of a node.

Where,

E_{max} and E_{min} = Maximum and Minimum energy levels in the neighborhood

E_{node}= Node's residual energy level

REL is an approximate rank function [7] that indicates the energy ranking of a node among its neighbors. Higher the *REL*, lesser is the energy-criticality of a node. Nodes exchange energy information by piggybacking their current energy levels on interest and data messages (energy value can also be included as one of the attribute values), and each node maintains a cache for storing neighbor residual energy levels. The implementation complexity is negligible.

2) Traffic Intensity, $TI = \frac{Traffic\ in\ node's\ queue}{Maximum\ queue\ size\ of\ the\ node}$, representing the traffic burden on a node.

Lower the *TI*, lesser the data-criticality in a node. The queue size includes the application traffic and also the traffic that a node has already committed to forwarding.

Both *REL* and *TI* lie in the range [0-1] and jointly define the criticality of a node. For example, a node with low *REL* and high *TI* is a critical node, since the remaining energy resources might only be sufficient for the large pending traffic and it may therefore be appropriate to reject any further forwarding requests.

Fuzzy membership functions [8] were used to map the computed parameter values to three discrete fuzzy values; low, medium and high. A Mamdani rule [8] base was then established to express all possible parameter associations and the corresponding fuzzy decisions. The association matrix is repeated in table 1.

TABLE 1
Rule Table: Fuzzy associations for interest forward

REL \ *TI*	Low	Moderate	High
Low	*p*	0	0
Medium	1	*p*	0
High	1	1	*p*

In the table, *p* represents the line of criticality; the initial experiments were done with three degrees of conservativeness: p = {0, 0.5, 1}. Finally the probability of interest forward (the final response) was computed using the centroid method [8]. Documentation in [6] provides a complete explanation of the logic design, with all mathematical and pictorial depictions.

C. Sample Result

Fuzzy diffusion was implemented in ns2 [9] and its performance was compared with directed diffusion. Figure 1 shows a sample performance result from the introductory work [6], where an approximately 15-30% increase in simulated network life time was noticed in fuzzy diffusion.

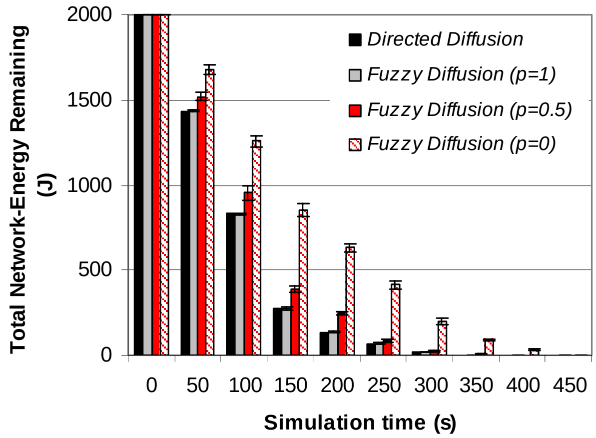

Figure 1. Residual Network Energy

The results clearly substantiated the need for diffusion nodes to be highly conservative when there are abundant alternate paths, since only one needs to be reinforced for contributing to the application task. Fuzzy diffusion exploits the fact that in a dense, high traffic network not every node needs to participate in data communication to achieve the required level of performance. Significant routing redundancy is inherent, which could be exploited to conserve energy and save critical nodes.

D. *Fuzzy Diffusion Analysis*

In this paper we extend the initial exploration on fuzzy diffusion to experimentally verify the following hypotheses:

Research hypothesis 1: *Decision making tools play a significant role in fuzzy diffusion performance. Methods that consider network parameter interdependencies and provide gradual state transitions yield better performance. .*

Research hypothesis 2: *Fuzzy diffusion would be appropriate only in dense, high traffic sensor applications characterized with abundant traffic and routing redundancies, wherein fuzzy forwarding decisions would make an impact on the network performance.*

In the performance quantification of fuzzy decisions, we use a straightforward crisp decision making (explained in section III.*B*) as the comparison baseline. For convenience, this paper refers the crisp decision strategy embedded diffusion algorithm as crisp diffusion.

Analyzing the network scenarios under which fuzzy diffusion would be applicable is important, since any application-aware protocol needs to be matched with the application in which it would be most effective. Diffusion experiments in [4, 5] state that; *when sensor network protocols are designed to suit and exploit application characteristics, a generalized solution (single protocol for all applications) does not exist. A family of protocols needs to be designed, and experimental quantification of their performances in different applications should be provided.* Employing an application-specific protocol in mismatched scenarios can considerably degrade the network performance, since the protocol methods might be rendered ineffective due to the lack of application characteristics that the protocol was originally designed to exploit.

III. Decision Strategies

In this section we provide a simple mathematical characterization of the decision making tools employed in this investigation. The primary goal is to analyze the efficiency of interest forwarding decisions provided by the fuzzy and crisp logics, and so the significant measure to quantify would be the final response (probability of interest forward, P_f) distribution, for each of these algorithms.

A. *Fuzzy Decision Logic*

Figure 2 depicts the behavior of the fuzzy algorithm (distribution of P_f as a function of *REL* and *TI*) for *p* value 0.5. The pattern of distribution will be the same for any choice of *p*.

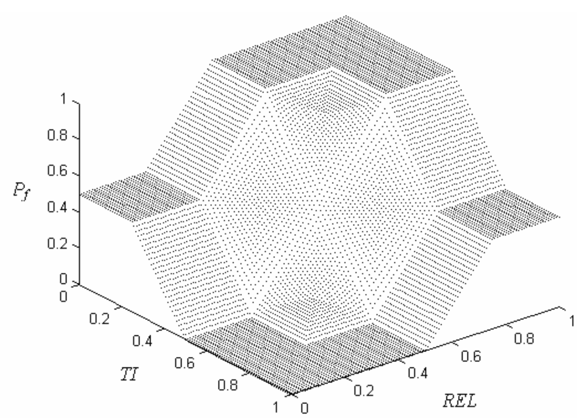

Figure 2. P_f Distribution for Fuzzy Logic

The distribution can be easily viewed in three fuzzy segments of criticality; low, medium and high. A response of zero for high degree of criticality, a response of one for low degree of criticality and a linear combinational response for medium criticality. The linear region represents a gradual transition between the high and low regions. The fuzzy association table takes into consideration all possible parameter interactions, and the centroid method of response estimation computes the centroid of the area covered by the criticality sets (low, medium, high) for each parameter. Fuzzy logic collectively provides smooth state transitions as the parameters vary.

The parameters *REL* and *TI* jointly define node criticality, and the distribution clearly shows that fuzzy logic takes into consideration the parameter independencies. In a real networking environments multi-parameter correlation might be extremely significant.

For example, a node with low *REL* can still be considered a non-critical node, if its *TI* is zero. Since an empty queue suggests that the node has not sourced data or committed to other data forwarding, with high probability, it could spend its remaining energy resources on data forwarding to satisfy the application task. In the graph, for *REL* and *TI* values at the low end (around zero), the probability of forwarding an interest is 0.5, providing a rational thinking of the network state. This decision making is intended to mimic human thinking process and not be purely robotic.

B. Crisp Decision Logic

Crisp logic would provide a less complicated binary rule for routing decisions. "Crisp decision making" uses computed parameter values directly to estimate node criticality, rather than mapping them to fuzzy logical values. The probability of forwarding an interest is estimated from a binary rule base (0 or 1) based on a simple linear combination of the node parameters rather than any compound equations as in the centroid method. One possible method of crisp decision making is described below.

The Degree of Criticality (DoC) can be estimated as

$$\text{DoC} = 1 - (\alpha * REL + \beta * (1 - TI))$$

Where α and β are the weights (in range [0-1]) associated with each parameter, subject to $\alpha + \beta = 1$. For this investigation we consider $\alpha = \beta = 0.5$, assuming that *REL* and *TI* are equally significant in defining the criticality of a node.

Final decision could be computed from a crisp rule base as:

If (DoC <= 0.5) Then $P_f = 1$
Else If (DoC > 0.5) Then $P_f = 0$

The distribution of P_f for the crisp decision logic is shown in figure 3.

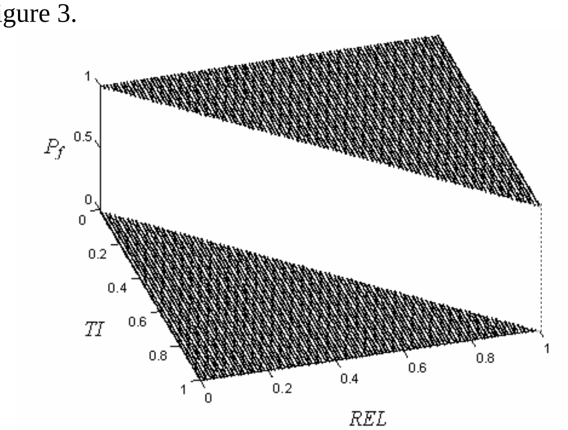

Figure 3. P_f Distribution for Crisp Logic

The distribution exhibits a step curve, where the final response (probability of forwarding) switches from 1 to 0 or vice-versa, at a particular threshold of the input parameter combination. The behavior does not provide a gradual transition segment between the two extreme responses as provided by fuzzy algorithm. The smooth transitions in fuzzy logic were made possible by the membership function mapping of the entire range of parameter values into low, medium and/or high logical values. Since crisp does not consider any parameter interdependencies, it does not provide any modulated decisions.

C. Discussion

Naturally crisp decisions involve less processing, but sensor nodes generally prefer to perform significant local processing if they can thereby reduce packet transmissions, since for short range WSNs, data processing is much cheaper than radio communications.

Pottie and Kaiser [2] show that energy consumed in transmitting a 1 kilobit packet over 100m is approximately the same as processing 3 MIPS on prototype wireless sensor nodes (The radio/processor power draw specifications for the popular MICA sensor motes can be referred from [10]). Therefore if the fuzzy decisions prove to be significantly efficient in making reliable routing estimates, then the amount additional processing incurred by would be justified.

This section defined the behavior of the two decision tools. Several other tools in the same order of complexity as fuzzy logic might provide similar performance, but the purpose of this analysis is to compare fuzzy logic against the simplest form of decision making (1 or 0), and verify if there is perceivable performance difference. Only a significant improvement would justify the use of the fuzzy mechanism (or another of similar complexity).

IV. PERFORMANCE ANALYSIS

For the purpose of experimental quantification of the stated hypotheses (in section II.*D*), this investigation provides analysis under the following network settings:

1. Performance evaluation of crisp diffusion under the same network setup that was used to analyze fuzzy diffusion in [6]. The crisp decision making algorithm was embedded into ns-2 [9], and the simulation was configured with the same parameter values as in [6] (repeated in Table 2 for convenience). Figure 4 shows a simplified structure of the fuzzy and crisp decision diffusion modules.

TABLE 2
SIMULATION PARAMETERS

Number of nodes	100, scattered uniformly in the field
Topography	1400m by 1400m large target area of surveillance
Radio range of nodes	250m
Channel bandwidth	1.6 Mb/s
Simulation run time	600 seconds
Initial energy of nodes	20 Joules
Transmission power consumption	660 mW
Reception power consumption	395 mW
Idle power consumption	39 mW
Number of sources and sinks	10
Event (data message) size	64 bytes
Interest size	36 bytes
Interest generation rate	1 per 30 seconds
Event rates (exploratory and high)	Same as in [4]

2. Analysis of fuzzy diffusion under low-traffic network scenarios to measure its suitability to such applications. The experiments were repeated with the fuzzy controller in *one-phase-pull* diffusion application (versus the origi-

nal two-phase pull) under two scenarios: 1) the same configuration setup (table 2) and 2) just one sink to significantly reduce network traffic.

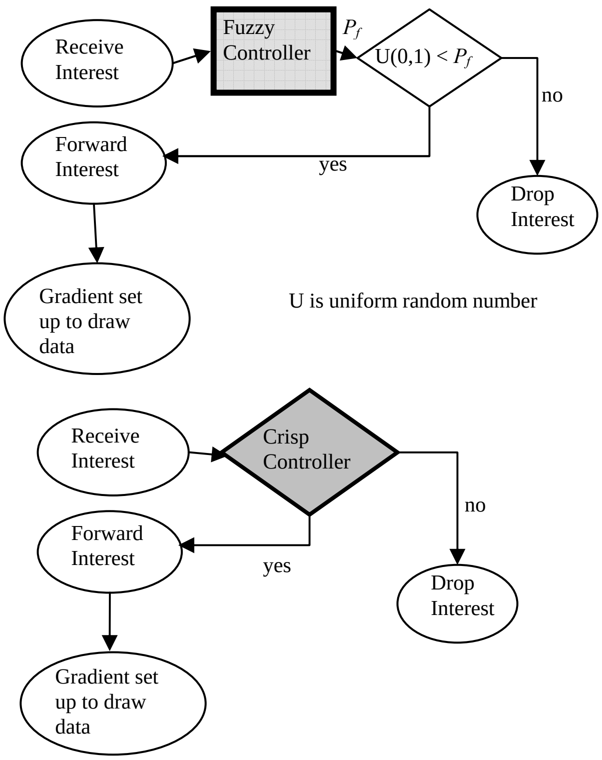

Figure 4. Rule Base in Diffusion

The sub-sections A and B present the results of experiments of 1 and 2 respectively.

A. *Fuzzy Logic Performance*

In this section we evaluate the choice of fuzzy logic as a decision making tool independently from the introduction of adaptive forwarding decisions in the diffusion process. Figures 5, 6 and 7 compare the performances of fuzzy and crisp diffusion schemes. Fuzzy diffusion with p=0 (highest degree of conservativeness) was chosen, since the initial results [6] proved that extreme conservation was indeed the best performing gradient for high traffic applications. The results of fuzzy and directed diffusion are repeated from [6]. Crisp diffusion, as mentioned before, was run with the identical simulation setup. The performance results were obtained with 90% confidence intervals [7]. The graphs should be viewed as a relative comparison of crisp and fuzzy diffusion with directed diffusion as the bench mark.

The results show substantially increased performance in both energy savings and data delivery performance for fuzzy diffusion as compared to crisp diffusion. In most cases the confidence intervals of directed and crisp diffusion schemes overlap, implying that adaptive forwarding, without fuzzy logic, achieves no significant performance improvement from directed diffusion.

The results suggest that sharp decision transitions in node criticality estimations may not be appropriate for adaptive routing decisions where multiple parameter inter-dependencies need to be taken into consideration. For example, a degree of 0.49 should not be considered strictly non-critical when 0.51 is estimated as critical. We need more nuanced assessments that enable graceful node status transitions and fewer oscillations in the decisions.

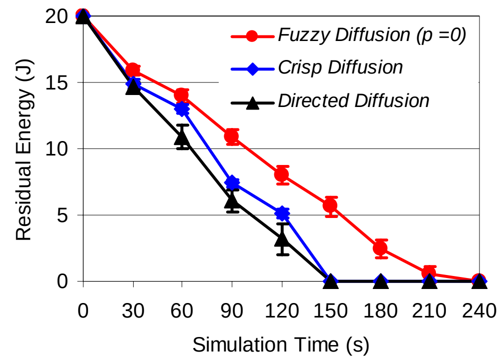

Figure 5. First Dying Node's Energy Profile

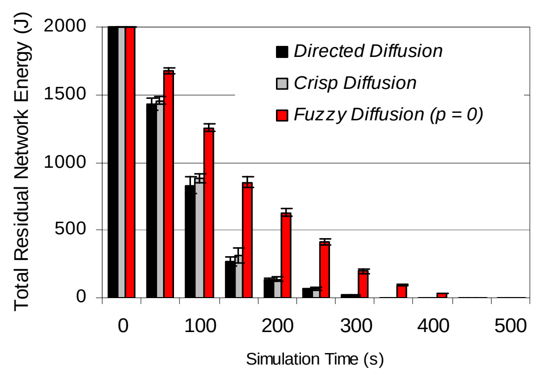

Figure 6. Residual Network Energy

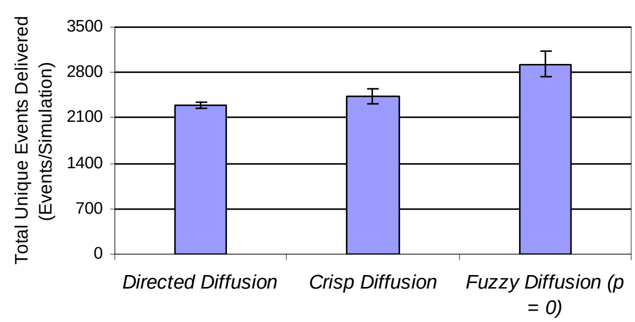

Figure 7. Information Delivery Efficiency

Fuzzy decision strategy provides a simple, yet efficient, inter-dependency modeling. The analysis suggests that the use of fuzzy-like decision tools to provide reliable estimates of the node criticality may extract better performance than binary decisions. Efficient resource-adaptive decisions contribute to significant reduction of network radio transmissions; thereby prolonging net lifetime and connectivity.

B. *Fuzzy Diffusion Applicability*

As mentioned before, since fuzzy diffusion is an application-aware (data centric) routing protocol, it is imperative to quantify its performance under different application settings. The initial investigation [6] selected the two-phase-pull [5] diffusion algorithm, which generated abundant traffic during the simulation run (due to data flooding), which represented high traffic application scenarios. The conservative approach by fuzzy diffusion proved extremely energy efficient in such networks, since reducing redundant transmissions significantly amortized network traffic.

One-Phase-Pull Diffusion

One-phase-pull [5] is a source-based reinforcement algorithm that eliminates the entire phase of exploratory data flooding from the two-phase-pull variant. The sinks flood interest throughout the network, establishing gradients for data dissemination from source to sink. The source nodes instead of flooding exploratory data (as in two-phase-pull), choose the lowest latency next-hop gradient and immediately send high-rate data. This is repeated at every hop until the sink node is reached. Thus the reinforcement phase is completely eliminated and a lowest latency path is explicitly chosen from source-to-sink direction. The main advantage with two-phase-pull is that it estimates the best latency path based on data flood on both directions (interest, exploratory data), and so is robust against asymmetrical links. One-phase-pull trades off this advantage to eliminate the excessive transmission overhead due to the exploratory data flooding.

One-phase-pull would be ideal for applications that can compromise link quality, but place strict constraints on traffic generated during path establishment. For example, in telemetry or military sensor networks deployed with varied interests and rapidly changing requirements, distinct queries might be issued frequently. In such cases, excessive flooding on every query request might be expensive. Alternatively two-phase-pull could be employed in monitoring applications where interests are sent at long intervals (requirements do not change rapidly) and the task duration is long enough to amortize the initial flooding cost. For such cases the better link quality provided by two-phase-pull is preferred.

Fuzzy Decisions in One-Phase-Pull

In large diffusion networks, one-phase-pull represents a packet reduction optimization on two-phase-pull, since flooding is drastically reduced. It is of interest to embed the fuzzy controller into one-phase-pull to see the amount of performance difference and the impact of reducing network transmissions in a reduced traffic setup. Figures 8 and 9 show the results of fuzzy diffusion embedded in one-phase pull.

As expected, extreme conservativeness ($p = 0$) achieves the maximum network lifetime as nodes decline data forwarding with high probability. A maximum of only 11% increase in simulated net lifetime is achieved as compared to a maximum of 30% improvement [6] when fuzzy diffusion was running over two-phase-pull. This suggests that the magnitude of savings achieved by fuzzy diffusion may fall with the network traffic, since in lighter traffic scenarios a fuzzy algorithm that bases its energy conserving logic on reducing redundant transmissions is less effective. The same might hold true in sparse networks, since due to low routing redundancy, the amount of traffic generated, and the number of alternative gradients, would be less.

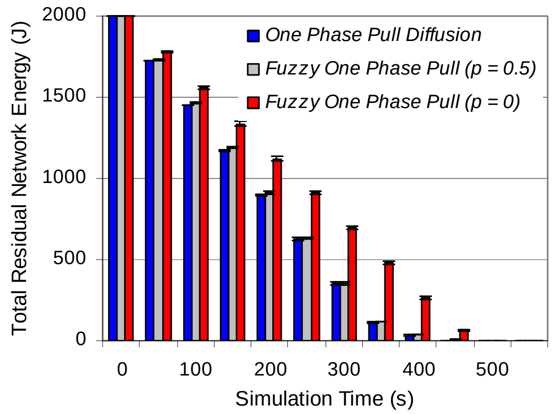

Figure 8. Residual Network Energy

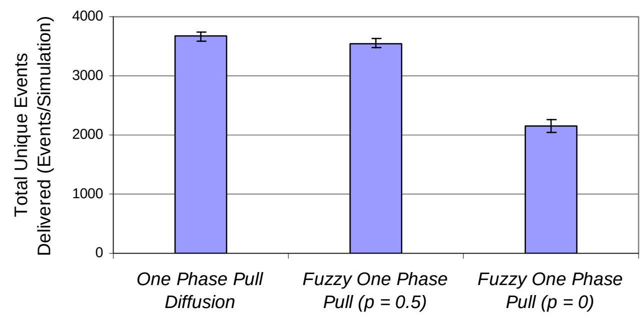

Figure 9. Information Delivery Efficiency

Another important behavior seen in these experiments is that extreme conservation actually degrades data delivery performance, unlike the results in [6], where significant improvement was seen. *Optimal path selection* (best latency path) is an inherent feature and strength of diffusion algorithms, which implicitly achieves considerable energy savings [4]. In fuzzy diffusion, nodes independently decline interests in the interest of conserving energy and therefore optimal data paths are not guaranteed. In such cases, the amount lifetime improvement achieved, and the volume of high-rate data information supplied during the excess network lifetime should be high enough to completely overshadow the performance degradation due to sub-optimal path possibilities.

The $p = 0.5$ case matched the data delivery performance of one-phase-pull diffusion, since reducing the conservation degree reduces the probability of sub-optimal paths. However, the energy graph suggests that a degree of $p = 0.5$ is not enough to achieve useful energy savings. Improvement in lifetime, while maintaining information delivery efficiency is the main goal of fuzzy diffusion, and insignificant energy conservation will not substantiate the use of fuzzy algorithm.

The $p = 1$ results are ignored, since the energy performance is much worse. The results clearly quantify that in one-phase-pull, only extreme conservation provided perceivable improvement in life time, but that too was not sufficient enough to supply high volume of data to overcome the degradation due to sub-optimal path formation.

To substantiate the claim further, same experiments were repeated with only one sink in the network. This approximately reduces the network traffic by a factor of ten as compared to the previous scenario. Figure 10 summarizes the performance results under the discussed network settings.

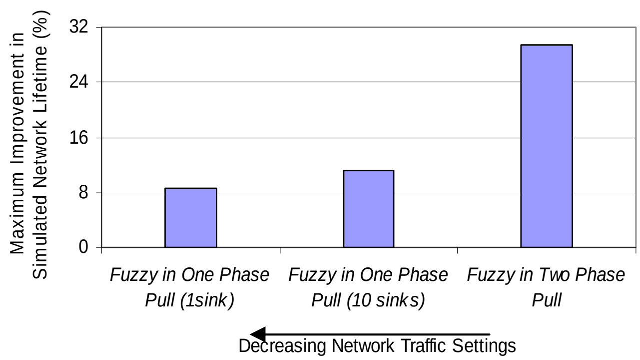

Figure 10. Performance Summary

As we can see, with one sink the lifetime improvement is further reduced. The performance is more than double with two-phase-pull application that generates heavy traffic as compared to other two cases, implying that: *fuzzy diffusion will be ideal for high event-rate, dense sensor applications (ex. periodic temperature monitoring), and that its effectiveness reduces proportionally with reducing network traffic.*

V. DISCUSSION

This paper presented two significant results from the progressing investigation on fuzzy diffusion [6]; 1) Substantiating the contribution of fuzzy logic in making graceful routing decisions and 2) Categorizing the applications that would benefit from fuzzy diffusion, and those that would not.

The results showed that fuzzy-logic provided rational estimates of network status, and was considerably better than sharp decisions in modeling the resource distribution of sensor networks. The investigation does not claim that fuzzy logic would be the superior decision making tool, but rather suggests that any decision tool chosen should incorporate parameter interdependencies for estimating node criticality. The decision algorithm should provide means for smooth state transitions and reliable final estimations. Fuzzy logic is one such tool.

Finally the application quantification clearly stated that adaptively reducing network radio transmissions, as in fuzzy diffusion, would be appropriate only in dense, high traffic sensor applications, where the volume of packets generated in the network and the abundant routing redundancies justify the use of amortizing radio transmission costs. The amount of energy savings reduces proportionally as the network traffic reduces, nullifying the significance of fuzzy adaptations.

A. Future Work

This investigation motivates the need to explore energy-aware strategies that will suit sparse or low traffic sensor applications. Though the work would be orthogonal to the current investigation, fuzzy based adaptations that might be applicable for such networks would provide a complete family of fuzzy-diffusion algorithms matched for different WSNs.

Fuzzy diffusion achieves energy efficiency in the query forward direction (interest dissemination direction from sink to source). Additionally, in the data-flow direction, there is a choice among multiple gradients at every hop (several non-critical nodes forward interests forming multiple gradients at each node), and the present diffusion schemes chose the lowest latency gradient to reinforce. Taking energy into consideration along with latency in choosing a neighbor gradient might improve net lifetime further. Fuzzy logic can be incorporated into the positive reinforcement phase of diffusion such that, at any instant, nodes with relatively high energy reserves could be reinforced to send data at high rate. Then we might have an optimal path from source to sink that represents an efficient trade-off between energy efficiency and latency.

Another significant realization during this research was the need for sensor oriented metrics. Though the energy and data delivery measures (used here) provide understandable performance estimates, metrics exclusively developed for application-aware sensor networks might be more intuitive. For example, a metric that quantitatively maps the amount of data delivered to the actual amount of distinct application information supplied would be useful for defining the exact data-centric performance. Further work on this investigation would try to develop such metrics and quantify fuzzy diffusion performance more precisely.

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