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U-GRAB: A UTILITY-BASED GRADIENT BROADCASTING ALGORITHM FOR WIRELESS SENSOR NETWORKS

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ABSTRACT

This paper addresses the problem of reliable transmission of sensed data through a vast field of small and vulnerable sensors towards a sink node. We concentrate in this paper on networks deployed rapidly in harsh environments as needed for instance in disaster-relief scenarios. Hence, emphasis has to be put on the minimization of the global energy consumption of the network and on providing both fast data transmissions and a rapid network setup. Therefore, we introduce a new gradient broadcasting routing algorithm for wireless sensor networks, U-GRAB, where the broadcasting decision is taken according to a utility-based policy. This policy favors the broadcasting of packets for nodes that experience non-congested channels and have a satisfactory energy level. Our simulation results show that this new forwarding strategy greatly improves the robustness/energy/delay trade-off of GRAB, the current state-of the art solution in gradient broadcasting techniques.

1. INTRODUCTION

The reliable transmission of sensed data across large-scale wireless sensor networks (WSN) has triggered lots of efforts in current research projects. Recent technologies offer low-cost and low-power chips that can be deployed for monitoring purposes in open fields. When a node senses some change in the environment, it advertises its data to one or several sink nodes. Due to the large scale of such networks, a multi-hop transmission is often used between the data source node and the sink. Therefore, the routing algorithms must provide robust end-to-end transmissions, which is even more important when nodes are deployed in environments with hazardous operational conditions (e.g. high temperature, fire, humidity...). In such conditions, nodes are prone to an increased number of failures and wireless transmission becomes less reliable.

In this work, we target applications with a high frequency of reception failures at the nodes due to severe working conditions, i.e. packets losses due to channel variability or node failures. In this context, traditional single path approaches such as Directed Diffusion [1] or Rumor routing [2] are not suitable. In this case, the source-sink path easily breaks, which triggers a new flooding stage for route discovery. Route repair techniques may in that case be applied [3], but such a strategy also introduces an additional delay for path repair. Moreover, we concentrate on scenarios where nodes have to be deployed rapidly, as for instance for disaster relief applications and in such conditions, the network has to be up and running as quickly as possible. Hence, there is no time for complex beforehand route computations and/or rate allocation as targeted in other robust routing techniques for WSN [4, 5]. To summarize, in this paper, we will concentrate on proposing a solution which adapts to the changing environment without triggering too much overhead at the network layer (and hence reducing the energy consumption of the network) while providing a quick network response. Reducing energy consumption and delay will affect the transmission robustness. Our design goal is to achieve the best possible robustness/energy/delay trade-off in the design of the routing strategy.

Robustness can be achieved through a hop-by-hop or an end-to-end acknowledgement procedure at the medium access or at the transport layer [6]. In this case, and for networks suffering from high packet losses, transmission delays due to retransmissions are increased drastically [7]. Since we have a stringent delay constraint, we disregard such options which are more suited to WSNs whose purpose is to monitor with a high fidelity a phenomenon where robustness transmission has to be guaranteed.

Another mean of introducing more robustness is by introducing totally redundant transmissions, either by defining redundant source to sink paths in the network or by allowing several nodes at a time to forward a packet based on given forwarding policies. Redundant source-sink paths are constructed in braided multi-path routing algorithms [8], [9], which are multi-path versions of Directed Diffusion. In these works, N routes are reinforced after the flooding stage and maintained with either 'keep alive' packets [8] or by alternatively sending the data in a round robin manner on each path to reduce the route maintenance load [9]. Such solutions, where routes have to be directly defined also introduce additional delay in the set up stage of the network.

To provide a rapid sensor network roll-out and quick transmissions, gradient broadcasting techniques are the most promising solutions (cf. [10, 11, 12, 13, 14]). In these approaches, no routes are set prior to sending data, and only costs are assigned to nodes being equal to the minimum cumulative link cost to the sink node. This network setup stage is very short and light in terms of overhead since only one broadcast per node is needed to create the cost field [11] When a sensor has some data to send, it broadcasts its data packet by assigning its own cost to the packet cost Q_p. The neighbor nodes *with costs smaller than the packet cost* Q_p decide to broadcast the packet or not, based on a set of forwarding rules. If the packet is broadcasted, its cost Q_p is updated with the cost of the forwarding node. All the cost values of the network create a gradient field with the lowest value located at the sink and all subsequent transmissions always *roll down the hill* to reach the sink. When several sink nodes exist, several cost fields are determined. The cost field is either set up by an a-priori flooding stage [10, 11, 13] or on-demand with a request / response packet exchange [14, 12]. The network setup is fast since a single flooding stage is needed to create the cost field. No complicated procedure is needed to create routes from sources to sink and hence no additional route repair procedures are implemented to guarantee robustness. Also, to deliver a fast network response, no hop-by-hop or end-to-end acknowledgements are considered. The statistical redundancy obtained to multiple packet forwards is supposed to provide enough robustness for the information to be gathered at the sink. Of course, there is a price to pay in terms of energy since more nodes participate in the forwarding effort. Hence, the policy chosen to decide whether a node closer to the sink forwards or not a message impacts the robustness / latency / energy trade-off and constitutes the heart of the protocol.

This work introduces a gradient broadcasting algorithm for wireless sensor networks, U-GRAB, relying on a utility-based forwarding policy where nodes decide to forward or not a message. Our aim is to improve the reference gradient broadcasting algorithm GRAB [11] which exhibits very good robustness statistics but at the price of a high energy consumption and transmission delay. To reduce the energy due to packet broadcasting, we introduce a utility-based policy that accounts for the current congestion of the channel and the energy level of the node. Hence, we are able to reduce the number of redundant copies while maintaining the same level of robustness as GRAB. Also, we aim at greatly improving the transmission delay compared to GRAB by reducing its constraint on the number of next hop neighbors receiving a packet to forward.

The proposed utility-based distributed policy can be analyzed within a game theoretical framework. The corresponding game is a non-cooperative game where the cooperative behavior of the nodes is enforced by means of a pricing function. This function selectively rewards nodes for forwarding based on their energy level and on the congestion of their channel. This game is closely related to the Santa Fe Bar Problem (SFBP)[15] where a congested resource, the bar, is shared by a set of agents, the bar customers.

We show that the exact derivation of the game equilibrium and obtaining a closed-form expression of all the parameters of the utility function is tedious. We propose instead a heuristic, utility-based distributed algorithm where the nodes adjust the parameters of their own utility functions depending on their current energy level. As performed in the GRAB algorithm, the gradient cost field is set up in the first stage by assigning a cost to each node depending on its distance to the sink. It is the forwarding stage of U-GRAB that differs from GRAB: once a node has the proper cost for broadcasting a packet, it decides to forward or not based on the utilities it gets knowing the congestion of the channel and its own remaining energy. The tacit cooperation induced by our distributed heuristic is shown to improve the energy expenditure of the whole network by efficiently spreading the broadcasting task among the sensors with higher energy levels.

The utility based policy of U-GRAB is presented in section 2 and its distributed implementation is in section 3. Simulation results are given in section 4 and a conclusion is drawn at the end of the paper.

2. THE U-GRAB ALGORITHM

The GRAB algorithm is one solution for reducing the number of forwarding nodes by defining a forwarding mesh using a credit based approach. Based on extensive simulations, we have compared the GRAB performance with the simplest version of a gradient broadcasting algorithm (referred to as BGB hereafter) where a node forwards a packet if its cost is smaller than the packet cost (i.e. it is closer to the sink). We have observed that GRAB needs less energy than BGB for reliable environments. In order to achieve the same robustness as the BGB algorithm when the probability of node failure increases, GRAB spends as much energy as BGB. GRAB is also about 2 to 3 times slower than BGB. This is due to the power adjustment feature of GRAB that only broadcasts the packets to reach a fixed number of $N_n = 3$ neighbors. Consequently, a communication uses more hops than BGB. Our aim is here to provide a gradient-based algorithm that: *i*) Reduces the number of forwarding nodes when the network is reliable, *ii*) Provides robust transmissions when the network becomes unreliable and *iii*) provides faster sensor-sink communications than GRAB. In the following, our proposed approach uses the same cost field setup strategy as GRAB. It differs from GRAB by its forwarding policy, i.e. regarding the rules that make a node decide whether to forward a packet or not if the packet cost is higher than its own cost.

A utility-based forwarding policy We consider a network of N sensors; notation $\mathcal{N} = 1,\ldots,N$, with $n \in \mathcal{N}$. Each sensor n shares the wireless channel with a set of neighbor nodes denoted $\mathcal{V}_n = 1,\ldots,V$, with $v \in \mathcal{V}_n$. When a node n receives a packet of cost $Q_P > Q_n$, the node has to choose a strategy s_n in the strategy set $S = \{0,1\}$ where:

- $s_n = 1$ corresponds to the action *Forward* packet,
- $s_n = 0$ corresponds to the action *Drop* packet.

Let $c_{\mathcal{V}_n}$ be the level of congestion of the wireless channel used by node n and its neighboring nodes in vicinity $\mathcal{V}_n$. The level of congestion for the channel is defined as the number of concurrent accesses on the channel at time t. In addition, let c denote the congestion limit of the channel. The channel is considered congested if $c_{\mathcal{V}_n} \geq c$ and not congested if $c_{\mathcal{V}_n} < c$. Let $0 \leq \alpha_n \leq 1$ denote the benefit value to sensor n for using the channel to forward a message and $0 \leq r_n \leq 1$, the reward for not wasting energy in rebroadcasting a packet. The utility function for node n is then given by:

$$u(s_n, c_{\mathcal{V}_n}) = \begin{cases} \alpha_n & \text{if } s_n = 1 \text{ and } c_{\mathcal{V}_n} < c, \\ \alpha_n - 1 & \text{if } s_n = 1 \text{ and } c_{\mathcal{V}_n} \geq c, \\ r_n & \text{if } s_n = 0. \end{cases} \quad (1)$$

Each sensor chooses the action that yields the maximum utility, knowing the values of the rewards and the congestion status of the channel. The choice of α_n and r_n shapes the behavior of the nodes. Hence, the expected utilities depend on the particular strategic choice s_n of node n, its reward α_n for using the channel, its reward for energy savings r_n and the congestion status $c_{\mathcal{V}_n}$ of the channel which depends on the strategic choices of agent n and its neighbors.

This utility function can also be defined by introducing a negative externality E to show the influence of the congestion on the channel. If the channel is congested (i.e. $c_{\mathcal{V}_n} \geq c$), $E(c_{\mathcal{V}_n}) = 1$ and if the channel is free (i.e. $c_{\mathcal{V}_n} < c$), we have $E(c_{\mathcal{V}_n}) = 0$. With this notation, we can define the payoff as:

$$u(s_n, c_{\mathcal{V}_n}) = s_n\left[\alpha_n - E(c_{\mathcal{V}_n})\right] + r_n.(1 - s_n) \quad (2)$$

We want the reward for not forwarding r_n to provide more benefit to a node that has low remaining energy. Hence nodes with a lower residual energy level are not inclined to broadcast while nodes with full batteries get a better utility for broadcasting. Consequently, we define r_n as the ratio of the energy already consumed E_c to the initial available energy E_0: $r_n = E_c/E_0$.

A game theoretical perspective In the game model corresponding to the utility-based policy of Eq. (1), the nodes are the players that choose among two strategies, *Forward* ($s_n = 1$) and *Drop* ($s_n = 0$). If the payoff of *Forward* is larger than the payoff of *Drop*, the sensor transmits, otherwise the sensor drops the packet. We consider that a sensor has always some data to send. The game is repeated for each packet transmission. Since r_n is a function of the energy consumption at node n, the equilibrium of each repeated game is changing for each stage of the game. In this section we derive the mixed-strategy Nash-Equilibrium (NE) for one particular stage of the game, i.e. having r_n and α_n values fixed. Since the game is a finite strategic form game, a mixed-strategy NE exists.

Our utility-based policy is inspired by the Santa Fe Bar Problem (SFBP)[15] where a congested resource, the bar, is shared by a set of agents, the bar customers. The customers enjoy their evening at the bar only if it is not over crowded (i.e. the capacity of the bar is lower than a fixed limit c). The main difference with the forwarding game is that a player's decision impacts the congestion of the channel for only a subset of the players, i.e. the neighboring nodes. Moreover, due to the overlapping of coverage areas, some nodes contribute to several 'channels'. Therefore, some nodes in a set of neighbor nodes sharing the channel may sense a congested channel while others see it free. As a consequence, the nodes that receive the same packet to forward do not necessarily have the same view of the level of congestion of the channel. Further, in the SFBP problem, $r_n = 0$ and there is no reward for not attending the bar. We recall that this reward is introduced to account for the energy depletion of a node and reduce its incentive to forward and cooperate when its energy is low.

Nash-Equilibrium analysis Given $\{\alpha_n, r_n\}_{n\in[1..N]}$, the expected payoff a sensor n gets from selecting the action *Forward* is given by

$$\mathbf{E}[u(1,c_{\mathscr{V}_n})] = \alpha_n.P(c_{\mathscr{V}_n} < c) + (\alpha_n - 1).P(c_{\mathscr{V}_n} \geq c)$$

with $P(c_{\mathscr{V}_n} < c)$ (resp. $P(c_{\mathscr{V}_n} \geq c)$) the probability that the channel is free (resp. the channel is congested). Since $P(c_{\mathscr{V}_n} < c) = 1 - P(c_{\mathscr{V}_n} \geq c)$, we have:

$$\mathbf{E}[u(1,c_{\mathscr{V}_n})] = \alpha_n - P(c_{\mathscr{V}_n} \geq c) \tag{3}$$

The expected payoff for playing *Drop* is given by:

$$\mathbf{E}[u(0,c_{\mathscr{V}_n})] = r_n \tag{4}$$

A sensor will maximize its own payoff by forwarding if $\mathbf{E}[u(1,c_{\mathscr{V}_n})] > \mathbf{E}[u(0,c_{\mathscr{V}_n})]$. Thus, we have:

$$\alpha_n - P(c_{\mathscr{V}_n} \geq c) > r_n \tag{5}$$

We consider a mixed-strategy equilibrium where each sensor n has a different equilibrium probability p_n of playing *Forward*. This assumption is due to the fact that in a realistic network, the reward $r_n = E_c/E_0$ is likely to be different for every node as it is a function of the traffic a node has transmitted previously. The set of probabilities of forwarding p_n can be expressed by:

$$p_n = \text{Prob}\left[\alpha_n - P(c_{\mathscr{V}_n} \geq c) > r_n\right] \tag{6}$$

Since r_n is fixed for all the nodes trying to access the channel at the same time, the equilibrium is completely determined by the values of the reward of forwarding α_n of all the nodes. If a clear relation between the vector of α_n and the p_n can be determined, the values of the forwarding rewards can be chosen such as for instance to maximize the probabilities of forwarding of the nodes knowing the distribution of the energy rewards of the nodes.

As shown by Eq.(6), p_n is a function of $P(c_{\mathscr{V}_n} \geq c)$, the probability of the channel being congested. This congestion probability is a function of the forwarding probabilities of all the neighbor nodes $\mathscr{V}_n$ of n. For each neighbor node, its forwarding probability also depend its own values of α_n, r_n and the forwarding probabilities of its respective neighbor nodes. Hence, we have $p_n = f(\alpha, r)$, where $\alpha = [\alpha_1, ..., \alpha_n]$ and $r = [r_1, ..., r_N]$. Further, the p_n values are also strongly influenced by the medium access control (MAC) protocol which modifies $P(c_{\mathscr{V}_n} \geq c)$ by properly scheduling the transmissions. Hence, deriving the distribution of the congestion probability is very complex since it depends on the distribution of the network, the physical transmission properties which determines the set of overlapping coverage areas, the MAC layer implementation and the flows being transmitted in the network.

The Nash Equilibrium solution for the forwarding probabilities in (6) has little practical value, as not enough information is available to accurately characterized all the parameters. Moreover, since the game is repeated with different r_n parameters, new probabilities have to be computed for each transmission. In the following, we propose a distributed heuristic approach for which nodes adaptively choose their transmission probabilities based on the value of α_n which is updated by the node n throughout its lifetime by measuring and interpreting the activity on the channel.

3. THE DISTRIBUTED U-GRAB HEURISTIC

Congestion measure The exact number of concurrent transmissions on the wireless channel at time t can not be inferred by a sensor. The sensor's radio has only a partial view of the channel occupancy. However, compared to the problem where the players don't know the number of consumers that will attend the bar, we have a first valuable hint on the congestion level of the channel at the time of the decision. This hint is the 'busy channel' information when listening to the channel just before sending a packet. Therefore we know that at least one sensor is already transmitting. When multiple channels are available (i.e for FDMA, CDMA systems), a channel per code / frequency can be considered. Therefore, a node can quantify how many channels are busy even though is does not know how many other sensors access each channel.

The medium access protocol we consider in this work has no acknowledgement and simply transmits a packet after a random backoff time. It is able to detect activity on each channel (frequency/code) and provide such information to the routing layer using a cross-layer data exchange. In the simulations, we consider that there is only one common communication channel and hence $c = 1$.

In the proposed algorithm, we consider the sensed level of congestion c_n as an estimate of the real level of congestion $c_{\mathscr{V}_n}$ of the network. We consider that a node chooses rationally its strategy as follows:

- if $c_n < c$, the network is considered as not congested and the payoffs for forwarding (i.e. $u(1,c_n) = \alpha_n$) and not forwarding (i.e. $u(0,c_n) = r_n$) are computed,
- if $c_n \geq c$, the network is considered as congested and the payoffs for forwarding (i.e. $u(1,c_n) = \alpha_n - 1$) and not forwarding (i.e. $u(0,c_n) = r_n$) are computed.

The node chooses the strategy that maximizes its payoff knowing its estimate of c_n. Whenever $u(1,c_n) = u(0,c_n)$, the

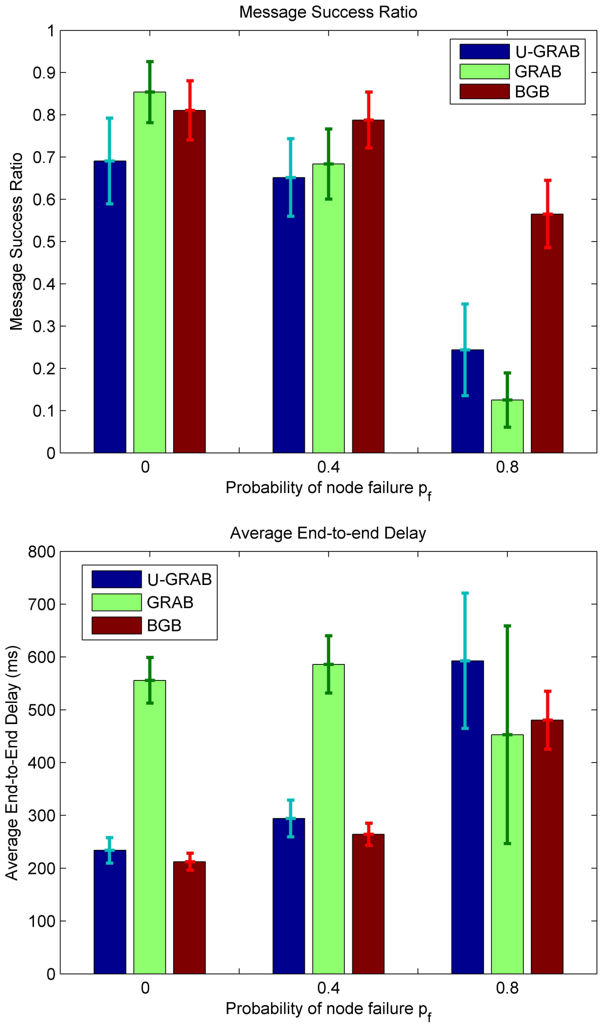

Figure 1: Performance of U-GRAB, GRAB ($F_\alpha = 10$) and BGB for $p_f = \{0, 0.4, 0.8\}$ in terms of robustness and average end-to-end delay.

sensor flips a fair coin to decide whether it should forward or not.

Choice of α_n We recall that if the channel is not congested, a sensor transmits if and only if $\alpha_n > r_n$, i.e. when the reward for forwarding is higher than the energy savings reward. α_n is interpreted in this heuristic as an energy threshold that allows a sensor to forward a packet or not, depending on the amount of energy remaining in its battery. When a sensor senses the channel to be free, the payoff function allows it to broadcast packets until $\alpha_n.100$ % of its energy is consumed. The sensor stops broadcasting packets whenever the energy reward becomes higher than α_n.

Once the energy level has reached α_n and the sensor has stopped broadcasting packets, it is allowed to increase its energy threshold α_n and resume broadcasting if it notices that its neighbor nodes do not forward any other messages he had received since he stopped forwarding. In this case, it believes that its neighbors with costs lower than its own cost do not forward anymore because their energy level is too low, too.

The value of the energy threshold of a sensor n obtained after k threshold increases, $\alpha_n(k)$, is computed according to $\alpha_n(k) = 1 - x_0.q^k$ where $q \in [0,1]$ and $x_0 \in [0,1]$, providing a first energy threshold $\alpha_n(0) = 1 - x_0$. As shown previously, the equilibrium of the problem depends on the value of α_n and r_n, an consequently on the choice of x_0 and q. However, their values are difficult to assess analytically in a real network as the values of r_n are not changing uniformly for all the sensors. Therefore, we have chosen $q = 0.75$ and $\alpha_n(0) = 0.25$ empirically after several tests to provide the best possible energy statistics.

A sensor decides to increase α_n if it notices that no other neighbor with a lower cost forwards a packet. To detect such an event, each node counts the average number of packets N_{high} received from neighbor nodes with a packet cost Q_P that is higher than its own cost Q and the average number of packets N_{low} received by its neighbor nodes with a lower packet cost Q_P. If $N_{high} = 0$ there is no traffic on the network. But if $N_{high} > 0$ and $N_{low} = 0$, the current node gets packets to forward that its one hop neighbors do not forward. The values for N_{high} and N_{low} are estimated at runtime using an exponential moving average.

Note that there is a particular transmission scenario for a homogeneous network that leads to an oscillatory behavior. Such behavior is encountered when all the nodes have the same level of energy (the reward is constant $r_n = r$), the same values of α_n and they all share the same channel. In this case, all the nodes sense a free channel and transmit concurrently. Thus, the channel gets congested and the sensors decide not to forward in the next transmission trial. As the channel becomes free again, the nodes resume forwarding and all the messages collide again. Such a behavior is neither fair nor efficient as a sensor never gets access to the channel. However, this scenario is unlikely to arise in a real network because of 3 main reasons. Firstly, as the routing protocol is not slotted and a random backoff CSMA channel access scheme is used, the probability that all the nodes see the channel busy at the same time is very small. Secondly, the fact that the nodes do not have the same view on the channel congestion due to overlapping of coverage areas, further limits the occurrence of such scenario. Thirdly, the condition $r_n = r$ is met when the network is newly started ($r_n = 0$). But as the GRAB protocol starts with a first cost field setup stage, the distribution of the r_n values is not uniform anymore as the data broadcasting stage is launched.

4. SIMULATION RESULTS

This section compares the performance of U-GRAB with GRAB and BGB by focusing on severe environments where nodes are prone to failures. Node failure is modeled as a first approximation using a uniform probability where a node fails with probability p_f when transmitting a packet. In this case, all the nodes are affected identically and independently by the outage. Even if such uniform error distribution is not realistic, it provides a good first assessment on the performance of the algorithms.

Robustness, energy and end-to-end delay are assessed for a 1000-nodes network spread over a 500×500 meters area. Nodes are randomly distributed and simulation results are averaged over 100 runs. For every run, 30 randomly positioned events are created, triggering about 30 +/- 5 messages on average. All the protocols have been implemented with the OMNet++ simulator in a modified version of the SENSIM sensor network simulator presented in [16]. We enhanced the SENSIM simulator by adding a realistic radio layer model that accurately accounts for collisions originating from congestion and interference. Additional node failure is modeled with a uniform independent probability $p_f \in \{0, 0.4, 0.8\}$.

In Fig. 1 and Fig. 2, we compare the results obtained for U-GRAB with GRAB and BGB. Fig 1 shows robustness (i.e. message success ratio) and delay (i.e. average end-to-end delay) performance metrics. Fig. 2 provides energy consumption metrics by showing the total number of forwarded messages and the percentage of initial energy consumed during the transmission. Each sensor follows the specifications of a MICA2 Mote [17]. The GRAB algorithm with a credit factor $F_\alpha = 10$ is considered here as it provides the most robust transmissions and the shortest delay for this parameter value.

From Fig. 1, one can see that U-GRAB outperforms GRAB in terms of robustness when the network gets really unreliable. For $p_f = 0.8$, there is an 80% increase in the message success ratio when the utility-based broadcasting algorithm is used.

The average end-to-end delay is as low as the one provided by BGB for $p_f = 0$ and $p_f = 0.4$, i.e. about 2.5 times lower than the delay of GRAB. However, when $p_f = 0.8$, we observe a drastic increase in delay for U-GRAB. As nodes fail more frequently in this case, the direct paths break more often and the paths with more hops succeed by a successive adaptation to the congestion status of the network. On the contrary, since GRAB constructs paths with short distance hops, its average delay decreases for $p_f = 0.8$, resulting in a significantly worse message delivery ratio.

In terms of energy consumption, it is clear from Fig 2 that U-GRAB uses much less energy than either GRAB or BGB due to the reduced number of forwarded messages. For $p_f = 0.4$, there is a decrease of about 40% and 15% in the number of forwarded messages and the energy consumption, respectively. The decision to forward a message based on the game formulation which accounts for the congestion status of the channel provides energy savings compared to GRAB and BGB.

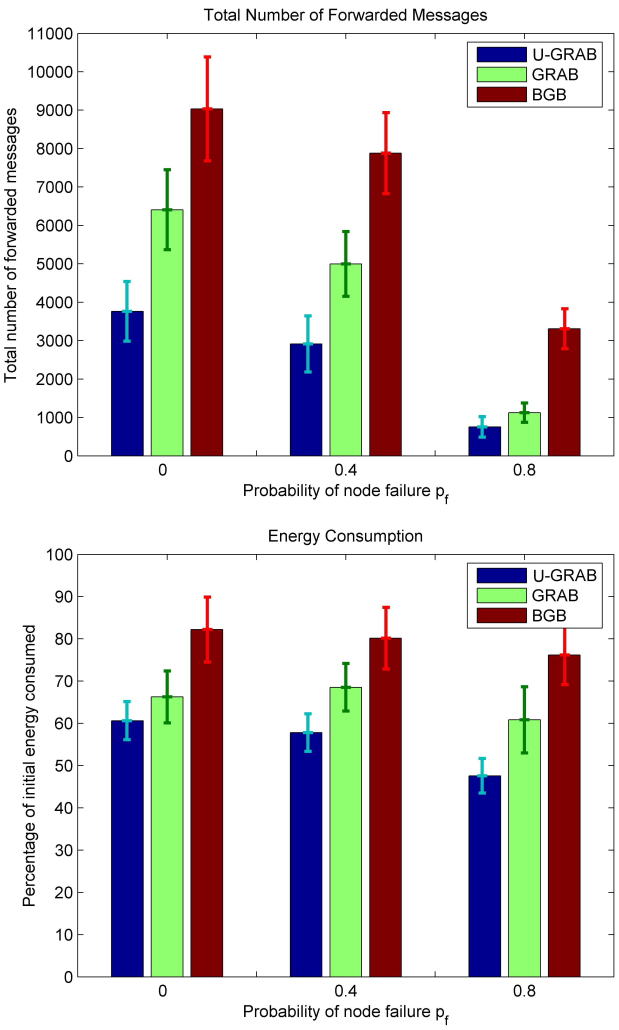

Figure 2: Performance of U-GRAB, GRAB ($F_\alpha = 10$) and BGB for $p_f = \{0, 0.4, 0.8\}$ in terms of the forwarding load and the average energy consumption.

6. CONCLUSION

This work proposes a new non-cooperative game formulation for the forwarding stage of gradient broadcasting algorithms called U-GRAB. The implementation of the game accounts for the level of energy of a sensor and for the estimated congestion status of the network. These features significantly improve the energy expenditure of the network by reducing with as much as 40% the number of forwarded messages compared to the standard GRAB algorithm. U-GRAB also reduces the average transmission delay and improves robustness when the probability of node failures is high. Hence, the U-GRAB algorithm represents a good solution for WSN deployed in emergency situations where a fast, energy efficient and robust network setup and response is needed for networks working in a harsh environment. Since we focused on delay and energy-efficiency constraints, we can not guarantee a perfect robustness. However, we've been able to improve the robustness/energy/delay tradeoff under these constraints compared to GRAB. We will concentrate in our future work on further improving this trade-off by introducing a distributed multiobjective optimization algorithm at the routing layer.

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REFERENCES

[1] C. Intanagonwiwat, R. Govindan, and D. Estrin, "Directed diffusion: a scalable and robust communication paradigm for sensor networks," in *Mobile Computing and Networking*, 2000, pp. 56–67.

[2] D. Braginsky and D. Estrin, "Rumor routing algorithm for sensor networks," in *In Proc. of the first ACM Workshop on Sensor Networks and Applications*, October 2002, pp. 22–31.

[3] D. Tian and N. D. Georganas, "Energy efficient routing with guaranteed delivery in wireless sensor networks," in *Proceedings of IEEE Wireless Communications and Networking*, vol. 3, 2003, pp. 1923–1929.

[4] B. B. J.H. Zhu, K.L. Hung and F. Nait-Abdesselam, "Rate-lifetime tradeoff for reliable communication in wireless sensor networks," *Computer Networks*, vol. 52, no. 1, pp. 25–43, 2008.

[5] C. C. V. Srinivasan, P. Nuggehalli and R. Rao, "Cooperation in wireless ad hoc networks," in *Proceedings of the IEEE Infocom*, vol. 2, April 2003, pp. 808–817.

[6] F. Stann and J. Heidemann, "Rmst: Reliable data transport in sensor networks," in *Proceeding of IEEE International Workshop on Sensor Network Protocols and Applications*, 2003, pp. 102–112.

[7] J.-M. G. R. Zhang and K. Jaffrès-Runser, "Energy-delay bounds analysis in wireless multi-hop networks with unreliable radio links," INRIA Technical Report RR-6598 [arXiv:0807.4656], Tech. Rep., 2008.

[8] D. Ganesan, R. Govindan, S. Shenker, and D. Estrin, "Highly-resilient, energy-efficient multipath routing in wireless sensor networks," in *MobiHoc '01: Proceedings of the 2nd ACM international symposium on Mobile ad hoc networking & computing*, 2001, pp. 251–254.

[9] L. Bush, C. Carothers, and B. Szymanski, "Algorithm for optimizing energy use and path resilience in sensor networks," in *Proceedings of Wireless Sensor Networks*, 2005, pp. 391–396.

[10] M. Maroti, "Directed flood-routing framework for wireless sensor networks," in *Proceedings of Middleware 2004*, 2004, pp. 99–114.

[11] F. Ye, G. Zhong, S. Lu, and L. Zhang, "Gradient broadcast: a robust data delivery protocol for large scale sensor networks," *Wirel. Netw.*, vol. 11, no. 3, pp. 285–298, 2005.

[12] G. Chen, J. Branch, and B. Szymanski, "Self-selective routing for wireless ad hoc networks," in *Proceeding of IEEE WiMob'2005*, vol. 3, August 2005, pp. 57–64.

[13] J.-J. Lim and K. G. Shin, "Gradient-ascending routing via footprints in wireless sensor networks," in *Proceedings of IEEE RTSS '05*. Washington, DC, USA: IEEE Computer Society, 2005, pp. 298–307.

[14] R. Poor, "Gradient routing in ad hoc networks, unpublished."

[15] B. Mishra, A. Greenwald, and R. Parikh, "The santa fe bar problem revisited: Theoretical and practical implications," in *The Proceedings of the Summer Festival on Game Theory: International Conference*, 1998.

[16] C. Mallanda, A. Suri, V. Kunchakarra, S. S. Iyengar, R. Kannan, A. Durresi, and S. Sastry, "Simulating Wireless Sensor Networks with OMNeT++," Louisiana State University, Tech. Rep., 2005.

[17] "Crosbow technology. mica2 wireless measurement system."