Mean-field performance analysis of a hazard detection Wireless Sensor Network

Marcel C. Guenther, Jeremy T. Bradley
Imperial College London
180 Queen's Gate
London SW7 2AZ, United Kingdom
{mcg05,jb}@doc.ic.ac.uk

ABSTRACT

Wireless Sensor networks (WSNs) are often deployed to monitor emergencies such as forest fires or landslides. Naturally, such events can impact network performance by destroying sensors or otherwise limiting their transmission capabilities. Fail-safe WSN routing protocols can mitigate the effect by closing routing holes promptly. Our work presents a model of pheromone based, fail-safe WSN routing. In particular we use higher-order moment mean-field techniques to study network behaviour during topology changes.

1. INTRODUCTION

In hazard monitoring WSN applications [1, 2], where nodes frequently break due to physical impact or battery depletion, an important Quality of Service (QoS) constraint for routing protocols is to provide reliable, fail-safe service. Various fail-safe routing protocols have been suggested in the WSN literature [1, 3] each of which aims to balance different QoS demands. Many of these use decentralised route discovery mechanisms, which enable arbitrary source nodes to infer routes to sink nodes using only local neighbourhood information that can be acquired via beacon exchange [1]. Paone *et al.* [3] argue that such routing algorithms are similar to pheromone routes, used by foraging insects to establish paths between nests and food sites. Using pheromone as an abstraction of available neighbourhood data, Bruneo *et al.* [4] created a mean-field model that investigates how fast fail-safe WSNs can establish routes and how node failures affect connectivity in different spatial areas. The model presented here extends their idea. Our model further allows us to study the transient effects of route establishment as a result of node failures, for instance its temporary impact on latency and throughput behaviour. To do so, we use mean-field analysis methods to capture transient mean and standard deviation for some of these performance metrics. While the model used in this study is similar to the one presented in [5], the main difference is that we concentrate on transient effects caused by changes in routing.

Our main motivation for extending the expressiveness of mean-field analysable models is the restricted scalability of low-level simulation techniques [6]. While the reminder of this paper focuses on the behaviour of our fail-safe model, we mention further research directions regarding efficient analysis techniques for WSNs at the end.

2. MODEL DESCRIPTION

Bruneo *et al.* [4] have shown that pheromone gradients can be represented by mean-field analysable models. As in their model, we assume that sink nodes emit pheromone and that non-sink nodes compute their own pheromone level based on their neighbours' pheromone intensity. So long as levels decrease with increasing distance from sink nodes, source nodes can send messages to sinks by forwarding packets to neighbours that have higher pheromone levels than they do. If several such neighbours exist, nodes will randomly choose between them to reduce hotspots. Should individual nodes fail, neighbouring nodes are no longer able to sense their pheromone level and learn to avoid them.

While in [4], the authors investigate how long topology reorganisations take and whether local routing holes persist, our model feeds back the routing decision of nodes to actively influence the message flow behaviour of the WSN. This enables us to study how node failures temporarily affect buffer occupancy and message delay, until the routing topology becomes stable again.

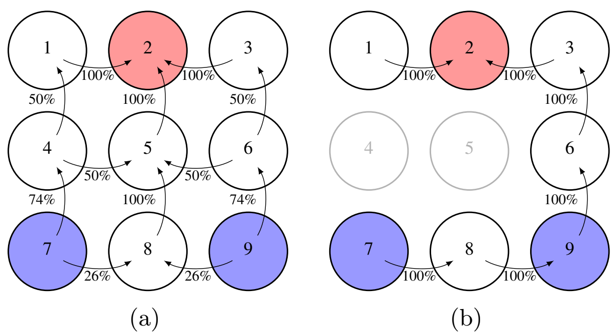

Figure 1: Steady-state routing in two different topologies. Node 2 is the only sink node, nodes 7, 9 two source nodes that have detected an event. Both the communication links and the proportion of messages routed via each link are shown. In Figure 1a all nodes function normally, whereas in Figure 1b, two nodes are assumed unavailable.

3. ANALYSIS

Figure 1 shows two topologies with different routing behaviour. In Figure 1a all nodes are functional, whereas in Figure 1b nodes 4 and 5 are not functioning.

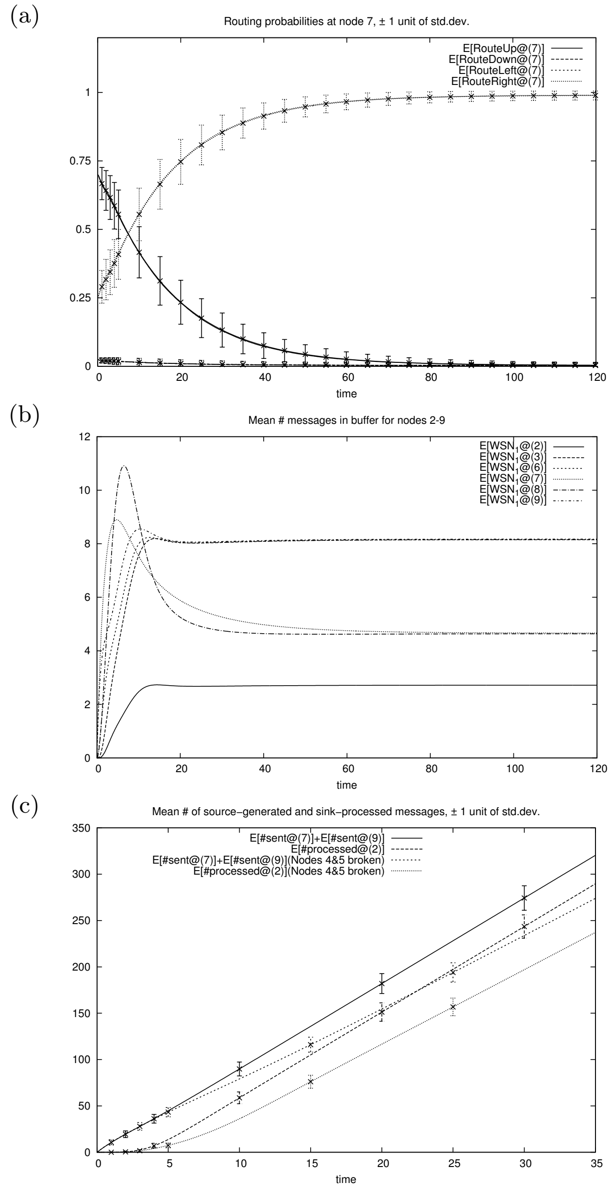

Figure 2: Figure 2a depicts the change in routing behaviour of node 7 after failure of nodes 4 and 5. Figure 2b shows the related temporary surge in buffer occupancy. Figure 2c illustrates the increase in latency following the failure.

Figure 2 shows the impact of the resulting topology reorganisation on the network performance. As can be seen in Figure 2b, the buffers of nodes 7 and 8 fill up temporarily due to the node failures until they have adjusted their routing around time 60 (cf. Figure 2a). Note that Figure 2b only shows the average buffer occupancy, so in reality we will experience even higher buffer levels. Figure 2c shows how the topology change affects the latency. As one would expect, even in steady-state the network with two broken nodes has a much higher end-to-end latency.

4. CONCLUSIONS

We have shown that the ideas presented by Bruneo *et al.* [4] can be extended to create a mean-field analysable model of a WSN that allows us to analyse the dynamics of fail-safe routing protocols during topology reorganisations.
Although we present a small-scale model here, we could easily scale our model to analyse WSNs with hundreds of nodes and less regular topologies. However, to do so, we would have to apply further numerical approximations to estimate higher-order moments without creating too many ODEs [7]. Generally, while first-order approximations are accurate in most situations, further research needs to be done to increase our understanding of when second and higher-order moments can be accurately computed using mean-field ODEs. In some scenarios, such as in Figure 2b, the second order moment ODE approximations did not match the simulation results. Further research into moment closures [8] may help to overcome these challenges. Moreover, in the future we intend to compare our mean-field results with low-level simulations and empirical data.

5. REFERENCES

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