Towards Predictable Real-Time Routing for Wireless Networked Sensing and Control

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Abstract—**Real-time routing is a basic element of closed-loop, real-time sensing and control, but it is very challenging due to dynamic, uncertain link/path delay. A basis of real-time routing is determining probabilistically guaranteed path delays, but this problem is NP-hard and it may well have to be solved by resource-constrained devices in a distributed manner; the highly varying nature of link/path delay makes it necessary to adapt to in-situ delay conditions in real-time routing, but it has been observed that delay-based routing can lead to instability and low data delivery performance in general. To address these challenges, we propose the minimum-delay (MD) algorithm that computes probabilistic path delay bounds in pseudo-polynomial time via dynamic programming, and the algorithm is amenable to lightweight, distributed implementation. For enabling adaptivity while addressing instability in real-time routing, we propose a multi-timescale-adaptation (MTA) framework that ensures long-term optimality while addressing short-term dynamics at the same time. We evaluate the performance of MD- and MTA-based real-time routing through a testbed of 130 TelosB motes, and we find it outperform existing real-time routing protocols by a significant margin, for instance, improving the packet delivery ratio and deadline catching ratio by a factor up to 6.04 and 6.67 respectively.**

I. Introduction

Besides deployments for open-loop sensing such as environmental monitoring, embedded wireless networks are increasingly being explored for real-time, closed-loop sensing and control. For instance, wireless networking standards such as the IEEE 802.15.4e, WirelessHART, and ISA SP100.11a have been defined for industrial monitoring and control [1]–[3], wireless sensor networks have been deployed for industrial automation [4], [5], and the automotive industry has also been exploring the application of wireless networks to intra-vehicular sensing and control [6]. In wireless networked sensing and control, message passing (or messaging for short) across wireless networks is a basic enabler for coordination among distributed sensors, controllers, and actuators. In supporting mission-critical tasks such as industrial process control, wireless messaging is required to be reliable (i.e., having high delivery ratio) and in real-time [7].

In multi-hop wireless networks, a basis for reliable, real-time messaging is real-time routing. Yet real-time routing in wireless sensing and control networks is significantly challenged by the dynamics and uncertainties in link/path delay, i.e., the time taken to successfully deliver a packet across a link or path. Not only do the inherent spatiotemporal wireless link dynamics and wireless interference introduce uncertainties in link/path delay, the dynamic network traffic pattern as a result of dynamic control strategies also leads to dynamic link/path delay [8]. The dynamics and uncertainties in link/path delay introduce fundamental challenges to real-time routing. Firstly, the dynamics and uncertainties make data transmission delay probabilistic in nature, yet, given the delay distributions of individual links along a path, the basic problem of checking the probabilistically guaranteed path delays is NP-hard [9], and this problem may well have to be solved by resource-constrained devices in a distributed manner. Secondly, given that data transmission delay is a highly varying metric and that it can change at a short timescale of each packet transmission, it is important to adapt to in-situ delay conditions in routing, but it has been observed that delay-based routing can lead to routing instability and low data delivery performance in general [10], [11].

Despite much work in throughput- or energy-efficiency-oriented wireless routing, real-time routing is much less studied. Moreover, the existing work that do consider data delivery delay in wireless routing either only try to minimize average path delay without ensuring probabilistic delay bounds [12]–[15], or they do not address the challenges that delay uncertainties pose to the task of determining probabilistic path delay bounds and the task of addressing instability of delay-based routing [16], [17].

To enable routing with probabilistic delay bounds in wireless sensing and control networks, we address the challenges of dynamic, uncertain delays in real-time routing. For the NP-hard problem of determining probabilistic path delays, we propose a pseudo-polynomial time algorithm *MD*. MD is based on dynamic programming, and it adopts the non-parametric quantile estimation algorithm P^2 [18] to estimate delay distributions along links and paths. The MD algorithm is amenable to lightweight, distributed implementation, and it enables identifying the paths that satisfy the required data delivery timeliness. For enabling adaptivity while addressing instability in real-time routing, we propose a *multi-timescale-adaptation (MTA)* framework: to ensure long-term optimality and reliability, the directed-acyclic-graph (DAG) for data forwarding is adapted at lower frequencies based on relatively slowly varying link property ETX (i.e., expected number of transmissions taken to successfully deliver a packet); at higher frequencies and based on the MD algorithm, the data flow within the DAG is controlled on a per-packet basis to minimize transmission cost and to ensure packet delivery within the required probabilistic delay bound. By enabling long-term optimality while addressing short-term dynamics at the same time, the MTA framework enables efficient, real-time routing in the presence of complex dynamics and uncertainties.

We implement the MD algorithm and the MTA framework in TinyOS, and we evaluate their performance in the high-fidelity sensor network testbed NetEye [19]. We find that real-time routing based on MD and MTA outperforms existing algorithms by a significant margin, for instance, improving the packet delivery ratio and deadline catching ratio by a factor up to 6.04 and 6.67 respectively.

II. Uncertainty-oriented real-time routing

In what follows, we first present the minimum-delay (MD) algorithm, then we discuss the multi-timescale-adaptation (MTA) framework.

A. Distributed satisfiability testing for probabilistic real-time guarantees

For real-time multi-hop routing, one basic issue is selecting paths which can ensure the required timeliness of data delivery. This is a challenging issue because the problem of checking probabilistically guaranteed path delays is NP-hard. That is, given the delay distributions of the individual links along a path, it is NP-hard to decide whether the probability of having a less-than-D path delay is no less than p [9]; this result holds whether or not the delays along individual links are independent. Existing work on probabilistically bounding multi-hop path delay have considered the most-probable-path (MP) problem where, given an multi-hop delay requirement D, the task is to find a path whose delay is less than D with the highest probability [20], [21]. Focusing on Internet QoS routing and given the nature of the MP problem, the existing solutions to routing with probabilistic delay bound are based on link-state routing and are not amenable to light-weight, distance-vector-type implementation [20], [21]. Nonetheless, link-state routing is usually not suitable for dynamic, resource constrained wireless sensing and control networks where reliable network-wide link-state update itself is a challenging issue and nodes may only have very limited memory space (e.g., up to 4KB of RAM).

To address the challenge of identifying paths with probabilistic delay bounds in resource-constrained wireless networks, we propose to first solve the *minimum-delay (MD) problem* where, given a node S, its destination G, and a probability p, the task is to identify the minimum delay bound $D(S, G, p)$ that can be guaranteed by some path(s) from S to G with a probability p. For the MD problem, $D(S, G, p)$ can be computed in pseudo-polynomial time via dynamic programming as follows:

$$D(S, G, p) = \min_{R \in \mathcal{R}(S), p \leq p' \leq 1} (D'(S, R, p') + D(R, G, \frac{p}{p'})), \tag{1}$$

where $\mathcal{R}(S)$ is the set of next-hop candidates for node S, $D'(S, R, p')$ is the p'-quantile of the link delay from S to R,[1] and $D(R, G, \frac{p}{p'})$ is the minimum delay from R to G that can be guaranteed with a probability $\frac{p}{p'}$. The intuition behind the above formulation is that, given a next-hop candidate R, if the probability of the transmission delay from S to R being no more than D' is p' and the probability of the delivery delay from R to G being no more than D is $\frac{p}{p'}$, then the probability of the delay from S to G via R being no more than $D' + D$ is no less than $p' \times \frac{p}{p'} = p$. The aforementioned formulation based on this intuition naturally lends itself to distributed, distance-vector-type diffusion computation which is suitable for resource-constrained devices. Additionally, the intuition does not assume independence between link delay distributions, and the mathematical foundation can be found from [22].

Of course, the simplicity of the aforementioned approach to the minimum-delay (MD) problem is based on computing an upper bound on the minimum-delay along a path instead of the exact minimum delay itself. Next-hop selection based on this upper bound on minimum-delay ensures real-time data delivery, which is critical in wireless networked sensing and control; our measurement study in Section III also shows that the computed upper bound is close to the minimum delay and the resulting real-time routing performs well in terms of real-time data delivery. For convenience, we denote the above method of computing probabilistic delay bounds as the *minimum-delay (MD)* algorithm.

Based on the distributed MD solution, a node S can identify the set of candidate next-hops (and thus paths), denoted by $N(S, G, p, L)$, via which the minimum delay from S to destination G is no more than L with probability p:

$$N(S, G, p, L) = \{R : R \in \mathcal{R}(S) \wedge \min_{p \leq p' \leq 1} (D'(S, R, p') + D(R, G, \tfrac{p}{p'})) \leq L\}. \tag{2}$$

Given that the probability requirement p tends to be high in wireless sensing and control networks, neighbors only need to exchange the tail instead of the complete distribution of their MD values. Thus the memory and communication overhead is low for implementing the distributed MD solution and for computing $N(S, G, p, L)$. Note that most existing delay-aware wireless routing protocols [12]–[15] consider mean delay instead of delay quantiles. This usually does not ensure the use of paths with small probabilistic delay bounds, because *smaller mean delay does not ensure smaller delay quantiles*. For typical traffic settings in the NetEye testbed [19], for instance, Figure 1 shows the non-negligible probability that, when the mean delay across a link ℓ_0 is less than that of another link ℓ_1, the q-quantile of ℓ_0's delay is greater than that of ℓ_1.

To realize the MD-based design, we need to estimate the quantiles of link delays. We propose to use data-driven link estimation [23] where samples of link delays are collected via MAC feedback for data transmissions. Then we use the *non-parametric P^2 algorithm* [18] to estimate quantiles. The P^2 algorithm is a memory- and computation-efficient algorithm that was originally proposed for the single-pass analysis of

[1] The link delay includes the queueing delay within node S and the transmission as well as propagation delay from S to R.

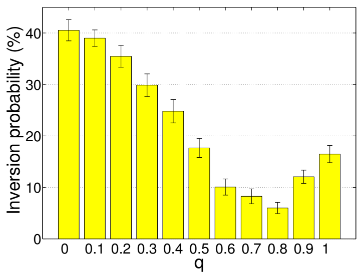

Fig. 1. Goodness inversion probability and its 95% confidence interval

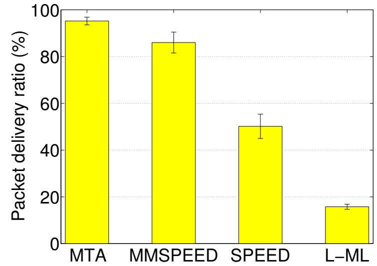

Fig. 2. Packet delivery ratio and its 95% confidence interval

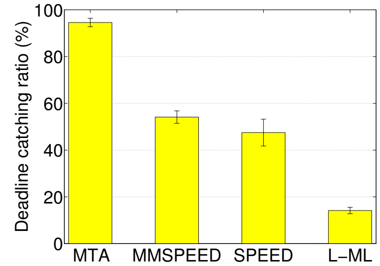

Fig. 3. Deadline catching ratio and its 95% confidence interval

large volumes of simulation data. Our measurement study in the NetEye [19] testbed has shown that the P^2 algorithm is very accurate in estimating delay quantiles (e.g., $\sim$0.5% estimation error) and is more accurate than parametric approaches as used in existing uncertainty-oriented QoS routing [21].

B. Multi-timescale adaptation

Real-time routing is subject to dynamics and uncertainties at multiple timescales. At a longer timescale, link properties vary as a result of changing environmental conditions (e.g., temperature); at a shorter timescale, data transmission delay varies on a per-packet basis, and bursty traffic may introduce sudden changes to network conditions. Robust system design usually requires adaptation to dynamics at the same timescale of the dynamics themselves. Yet we have found that, due to the highly-varying nature of link delays, routing using delay-based metrics can introduce large estimation errors and lead to routing instability as well as low performance [11]. To ensure long-term stability and optimality while addressing short-term dynamics at the same time, we propose a multi-timescale adaptation (MTA) framework for real-time routing as follows.

At lower frequencies, a directed-acyclic-graph (DAG) is maintained for data forwarding, and any path within the DAG is a candidate path for packet delivery. In particular, the data forwarding DAG is maintained based on link and path ETX (i.e., expected-number-transmissions to successfully deliver a packet) that reflect long-term system optimality and change relatively slowly compared with delay variation. There is a directed edge from node S to R in the DAG if and only if the minimum path ETX from R to the destination G is less than that from S to G. The DAG defines, for each node S, a set of forwarder candidates $\mathcal{R}(S)$ where $R \in \mathcal{R}(S)$ if link (S, R) belongs to the DAG.

At higher frequencies, the spatiotemporal flow of packets within the data forwarding DAG is adaptively controlled to ensure reliable, real-time data delivery in the presence of short-timescale dynamics such as transient packet losses and per-packet variations of link delay. More specifically, each packet contains information about the remaining time to deadline, denoted by L, and the required real-time guarantee probability p. When the packet reaches a node S, S first finds the set of forwarder candidates within the DAG, denoted by $N(S, G, p, L)$, that can ensure the real-time requirements p and L; then S forwards the packet using opportunistic routing with a subset of $N(S, G, p, L)$ that minimize the expected ETX in delivering the packet. Note that $N(S, G, p, L)$ is computed according to (2).

III. Measurement evaluation

We have implemented the MTA framework (including the MD algorithm) in TinyOS. To understand the real-time data delivery performance of MTA, we comparatively study MTA and the following protocols that consider delay in routing:

- MMSPEED: a geographic routing protocol that routes and schedules packet transmissions based on nodes' distances to destinations, packet delivery deadlines, and mean link delays [12]. MMSPEED also tries to improve packet delivery reliability by transmitting packets along multiple paths.
- SPEED: a geographic routing protocol where a packet is forwarded to a next-hop node at a probability monotonic to the enabled data delivery speed, where the speed is defined based on the distance progress towards destination and the mean delay from the sender to the next-hop node [13].
- L-ML: a distance-vector routing protocol where a path with the minimum average end-to-end delay is chosen [11].

In our evaluation, we use the NetEye [19] wireless sensor network testbed which consists of 130 TelosB motes. In this preliminary study, we let the two nodes that are farthest apart from each other serve as the source and sink node respectively; the source node generates one packet every second, and the real-time requirement is such that each packet be delivered to the sink within 1 second for at least 90% of the time. Each TelosB mote transmits at a power of -25dBm(a.k.a. power level 3 in TinyOS) such that the average number of hops between the source and sink is about eight in MTA.

Figure 2 shows the end-to-end packet delivery ratios in different protocols; for those packets that are received by the sink, Figure 3 shows the percentage of them that are received within the deadline. We see that MTA significantly improves the real-time data delivery performance, for instance, improving the delivery ratio and deadline catching ratio by a factor up to 6.04 and 6.67 respectively. One major reason why existing protocols have much lower deadline catching ratio is because they only consider mean delays instead of the probabilistic distributions of delays. Another reason for the low performance of the existing delay-based routing protocols is due to their instability in the presence of varying link/path delays; instability not only increases variability of data delivery delay, it also makes it difficult to precisely estimate link/path properties, and this is especially the case for L-ML which is a distance-vector protocol requiring end-to-end diffusion of routing control information such as link/path delays. Compared with SPEED, MMSPEED has higher packet delivery ratio because it uses multiple paths to forward packets; MMSPEED has higher deadline catching ratio because it uses speed-requirement-based priority scheduling.

IV. Concluding remarks

Through the MD algorithm and the MTA framework, we have addressed the two basic challenges that link/path delay uncertainties pose to real-time routing, that is, efficiently computing probabilistic path delays and addressing instability of delay-based routing. Besides demonstrating the effectiveness of the MD algorithm and the MTA framework, our testbed-based measurement study stresses the importance of considering link/path delay uncertainties in real-time routing. Based on the preliminary results discussed in this extended abstract, we are currently performing detailed study of the MD algorithm and the MTA framework to understand the impact that factors such as traffic pattern and timeliness requirement may have on real-time routing design. In our future work, we will study the interaction between real-time routing and real-time scheduling, and we will investigate related issues such as real-time capacity modeling and admission control to build a solid foundation for predictable real-time routing in wireless sensing and control networks.

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