Uncertainty Mitigation for Utility-Oriented Routing in Wireless Ad Hoc Networks

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***Abstract*— Link and node reliability are important metrics in wireless ad hoc networks. Therefore, evaluating and quantifying reliability has become the cornerstone of research in this field. Many existing wireless ad hoc network routing algorithms assume the availability of precise reliability information. This, however, is an unrealistic assumption given the dynamics of wireless ad hoc networks. Also, due to frequent changes in topology, reliability information is hard to collect, and oftentimes, inaccuracies can creep in. Therefore, a realistic method is needed to evaluate reliability by mitigating uncertainty in the estimation process. In this paper, we propose a novel reliability estimation model, account for uncertainty in the estimation, and design an uncertainty mitigation scheme. We then illustrate the effectiveness of our scheme in estimating reliability under various levels of uncertainty using a utility-oriented routing algorithm as a sample application. An extensive simulation study shows that the mitigation scheme significantly increases path stability and the long-term total benefit of the system.**

Keywords: Reliability, uncertainty, utility-oriented routing, wireless ad hoc networks.

I. Introduction

Wireless ad hoc networks operate in an infrastructure-less wireless medium that is subject to message loss. This message loss is usually represented by a single metric called link reliability. Various routing optimization problems have been formulated based on link reliability, with little or no information on how to obtain creditable reliability values. Usually, the reliability value is captured through a monitoring mechanism where the behavior of a node (and the corresponding links) is recorded by its neighbors. These mechanisms generally use a simplistic reliability estimation model for each link (i, j), which is the fraction of successful forwardings of link (i, j).

The reliability estimated in the above model has an uncertainty component caused either by an inadequate number of observations or by subtle changes in node behavior. A systematic way to characterize uncertainty in wireless ad hoc network environments remains unexplored. In this paper, we define an uncertainty metric to measure the possible variations and inaccuracies in the quantified reliability, and propose a scheme which uses dynamic threshold for uncertainty mitigation.

The dynamic threshold method operates in two phases. In the first phase, each node calculates a threshold for uncertainty which is decided based on its characteristics, associated cost, and expected return. A candidate set of nodes are chosen based on their uncertainty level. In the second phase, the best path is selected by applying the original optimization algorithm on the candidate node set. In this paper, we strictly restrict our discussions to the routing process. However, the proposed schemes can be used for mitigating uncertainty in any other optimization process in wireless ad hoc networks.

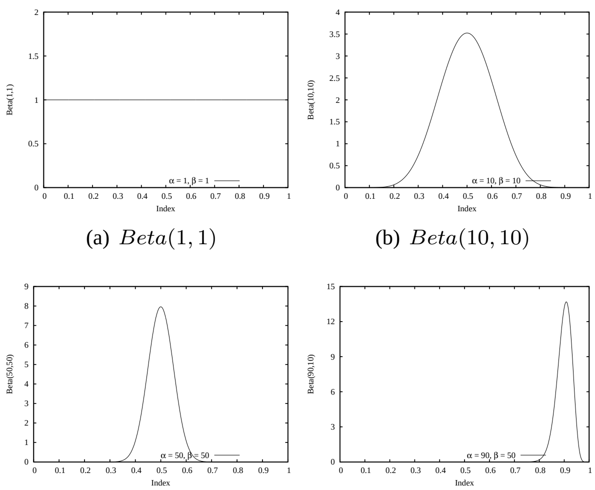
A utility-oriented routing model is used as a sample application to show the validity of our reliability estimation model using the uncertainty mitigation scheme. Different values of benefit reflect different qualities or priority requirements of routing requests. Each intermediate node has to incur a cost to relay a packet (e.g. cost in terms of energy). If the packet is lost during transmission, then no benefit will be obtained. In this sample application model, utility, defined as the expected benefit of a path, is the original routing metric. In computing utility, reliability plays a critical role. Therefore, our reliability evaluation model along with the uncertainty mitigation scheme benefits nodes by helping them to make informed decisions.

This work was supported in part by NSF grants CCR 0329741, CNS 0422762, CNS 0434533, CNS 0531410, and CNS 0626240. Correspondence Email: fli4@fau.edu.

II. Reliability Estimation Model

A highly dynamic environment and self-organizing nature are two important characteristics of wireless ad hoc networks that make the precise evaluation of reliability a critical issue in routing, QoS management, and intrusion detection. They make reliability information-gathering extremely challenging as well. The former leads to frequent changes in reliability while the latter enables nodes to change their behavior.

Neighbor monitoring is a unique mechanism that helps to evaluate reliability. Exploiting the promiscuous nature of broadcast communication in wireless media, nodes are able to track the outgoing packets of their one-hop neighbors through passive observation. When a node i sends a message through its neighbor j, the forwarding behavior of j can be monitored by node i. Similarly, j's behavior can also be monitored by any other node k that is a common neighbor of both i and j. If node i forwards a packet to the destination through j, i will classify the observation result as a success when i overhears j forwards that packet. Otherwise, i will consider it to be a failure. The corresponding variable, α for successful forwarding and β for failed forwarding, is incremented accordingly. However, it should be noted that a failure can occur for two reasons: failure of the link (i, j) or the selfishness of node j. In this paper we shall not distinguish between these two types of failure. Each



(a) $Beta(1,1)$ (b) $Beta(10,10)$

(c) $Beta(50,50)$ (d) $Beta(90,10)$

Fig. 1. The corresponding distributions.

node can then estimate its neighbor's reliability based on its accumulated observations using the Bayesian inference.

Bayesian inference is a statistical model in which evidence or observations are used to update or to newly infer the probability that a hypothesis is true. Beta distribution, $Beta(\alpha, \beta)$, is used here in the Bayesian inference. The beta distribution is a family of continuous probability distributions defined on $[0, 1]$ differing in the values of their two non-negative shape parameters, α and β. To start with, each node in the network has the prior $Beta(1, 1)$ for all its neighbors. As shown in Fig. 1, the prior $Beta(1, 1)$ implies that the distribution of the reliability metric p complies with the uniform distribution on $[0, 1]$, which indicates complete uncertainty as there are no observations. When a new observation is made, α or β is incremented. The prior $Beta(\alpha, \beta)$ is then updated.

III. Uncertainty Measurement

Many reputation systems use the Bayesian inference to reason nodes' trust opinion. However, these trust opinions are usually sharply divided into belief or disbelief. In this system, we introduce the concept of uncertainty and use a triplet to represent the node's opinion towards reliability: $(b, d, u) \in [0, 1]^3$ and $b + d + u = 1$ where b, d, and u designate belief, disbelief, and uncertainty respectively in the statement that the transmission between two nodes is reliable. It should be noted that the entire opinion space is divided into two regions: certainty $(1-u)$ and uncertainty u. The (b, d, u) will be derived from $Beta(\alpha, \beta)$ using the method below.

Two important attributes can be observed from the general understanding of the concept of uncertainty. First, when there is more evidence, which implies $(\alpha + \beta)$ is higher in our reliability estimation model, it consequently lowers uncertainty u. Second, when the evidence for success or failure dominates, there will be less uncertainty when compared to the situation in which there is equal evidence for both success and failure. After examining the major statistical metrics of the Beta distribution, we find that the normalized variance satisfies these observations. Therefore, we define u as follows:

$$u = \frac{12 \cdot \alpha \cdot \beta}{(\alpha + \beta)^2 \cdot (\alpha + \beta + 1)} \tag{1}$$

The numerator and denominator guarantee the latter and the former attributes respectively. The variance is multiplied by a constant 12, which makes $u = 1$ when $\alpha = \beta = 1$.

The total certainty is $(1-u)$ which can be divided into b and d according to their share of supporting evidence. Since the proportion of supporting evidence for the reliable transmission is $\frac{\alpha}{(\alpha+\beta)}$, b can be calculated as follows: $b = \frac{\alpha}{(\alpha+\beta)} \cdot (1 - u)$. Therefore, $d = (1 - u) - b = \frac{\beta}{(\alpha+\beta)} \cdot (1 - u)$.

In the Bayesian procedure, the probability that the next packet will be successfully forwarded by the corresponding neighbor is given as:

$$p = \frac{b}{1 - u} = \frac{\alpha}{\alpha + \beta} \tag{2}$$

IV. Uncertainty Mitigation Scheme

The design of our reliability estimation model defines uncertainty as the information ordering between no knowledge and total certainty to reflect the degree of confidence in the estimated reliability. Uncertainty is obviously unfavorable when we want to use the estimated reliability. In this paper, we propose a dynamic threshold scheme. To begin with, a node receives a request to participate in routing. The node then considers all possible next hop nodes and computes its uncertainty towards them using the accumulated observations. Then, threshold T is calculated to reflect its acceptable uncertainty level. Nodes with uncertainty above the threshold T are filtered out. From the remaining qualified nodes, the best node is chosen after running the original routing algorithm.

In our model, T is dynamic. Note that a static implementation of T is much easier. However, it is inflexible and contradictory to the general experiences of the uncertainty mitigation decision process. T should be dynamically determined based on the expected cost and return. This is necessary to accommodate the varying criticality of transactions. Intuitively, when the cost of a particular transaction is high, a node may not be willing to accept higher uncertainty. Also, when the associated returns are high, T will be pushed higher, and consequently, nodes accept more uncertainty.

The cost and the return are computed by node i after receiving the request. The expected gain is represented as $G \in [0, \infty]$. Let $\tilde{C}$ represent normalized cost, and $\tilde{C}$ equals the ratio of the cost a node is required to invest in a given transaction to the maximum amount of cost that a node can invest in a single transaction. To summarize this discussion, there are three parameters associated with each transaction: $\tilde{C}$, G, and u. A combination of any two of them can be used to derive the third. Formula 3 captures this idea well:

$$T = 1 - \tilde{C}^{\frac{G}{\lambda}} \tag{3}$$

Here, λ is the characteristic factor that reflects a node's attitude towards risk: conservative (a large number) or aggressive (a small number). A higher λ will lead to a lower T which makes the filtering more conservative. According to Formula 3, a larger $\tilde{C}$ will lead to a lower T. On the other hand, a larger G will lead to a higher T since $\tilde{C} \in [0, 1]$.

V. An Application: Utility-Oriented Routing

In utility-oriented routing [1], each routing is considered to be a transaction. Utility, defined as the expected benefit of the transaction, is chosen as the primary routing metric. This model sets up an ideal platform to demonstrate the effectiveness of our reliability estimation model and the uncertainty mitigation scheme. This is because, in utility-oriented routing, the primary routing metric is derived from reliability. In [1], reliability is assumed to be static and obtainable. We consider this to be a strong assumption. In our methodology, we relax this assumption and use a realistic reliability estimation model that takes into account the underlying uncertainty. In [1], there are two parameters that influence path selection: topology and packet value. However, using our reliability estimation model, two additional parameters influence path selection: uncertainty u and nodes' attitude λ.

A. Utility-Oriented Routing: Model Overview

We consider a source s that intends to send a packet to a destination k. s will get a benefit v if the packet is successfully delivered to k. For each link (i, j) in the graph, there are two associated properties: cost and reliability. Cost c_i^j is the energy needed to send packets with fixed size from i to j, while reliability p_i^j is the ratio of packets forwarded by j and the packets sent by i. For illustration, we first consider a single-link route from s to k with reliability p_s^k and cost c_s^k. Since k receives a packet with probability p_s^k, s has the same probability of getting the benefit v at the cost c_s^k. Note that s gets v if and only if the packet is delivered to k. From the economic point of view, the expected utility R of this route is the difference between the benefit and the route's cost, i.e.,

$$R = v \cdot p_s^k - c_s^k \tag{4}$$

Consider the multi-hop route $< s = 1, \cdots, k-1, k >$. Here, the utility is calculated as follows:

$$R = v \cdot \prod_{j=1}^{k-1} p_j^{j+1} - \sum_{i=1}^{k-1} c_i^{i+1} \prod_{j=1}^{i-1} p_j^{j+1} \tag{5}$$

A simple example in Fig. 2 illustrates the impact of topology, packet value, uncertainty, and nodes' attitude. Assume that in the following cases, all parameters are the same except those listed in the column 'different parameters' in Table 2. There are four possible route choices: $s-i-j-k$ (1), $s-i-j'-k$ (2), $s-i'-j-k$ (3), and $s-i'-j'-k$ (4). The last column in Table 2 indicates the path that is intuitively preferable for the scenario.

The topology of the network is reflected by the cost and reliability metric of each pair of nodes. The path with lower cost and/or higher reliability is always preferable. The influence of topology is shown in Case 1. In Case 2, one path has lower cost and lower reliability, and the other path has higher cost and higher reliability. The value of the packet will affect the decision of which path is preferable. When the estimated reliability metric is used, even when the topology parameters and packet value are the same, the paths may not be equally preferable as they have different underlying uncertainty. In Case 3, $s-i'-j-k$ is preferable over the other three paths since it has the lowest uncertainty. The impact of a node's attitude towards risk on route selection is presented in Case 4.

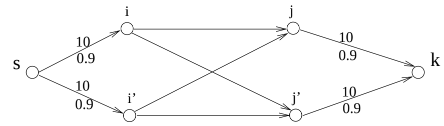


Fig. 2. An example illustrating the impact of different parameters on path selection. The cost and actual reliability values are shown on the link.

Table 2 Sample Cases

Case	c	p	λ	v	Different Parameter	Path
1	20	0.5	0.1	100	$c_i^j = 10$	(1)
	20	0.5	0.1	100	$p_i^j = 0.9$	(1)
2	20	0.5	0.1	100	$c_i^{j'} = 10$, $p_i^j = 0.6$	(2)
	20	0.5	0.1	200	$c_i^{j'} = 10$, $p_i^j = 0.6$	(1)
3	20	(10,10)	0.1	100	$p_{i'}^j$ =(99,99)	(3)
4	20	(10,10)	0.1	100	$\lambda_{i'}^{j'} = 0.05$	(4)

B. Application of the Reliability Estimation Model

A neighbor monitoring mechanism is employed to collect information for estimating reliability. While sending packets to its next-hop neighbor j, a node i will also try to over-hear and count the number of packets that j further forwards. If j forwards a packet sent by i, then i will consider this a successful forwarding and increment α_i^j. Otherwise, i increments β_i^j. When i needs to evaluate its utility and uncertainty for routing purposes, it will calculate (b, d, u) from the recorded α_i^j and β_i^j using the Beta function. Once the triplet is computed, Formula 2 is used to compute the estimated reliability. To keep the integrity of this evaluation method, the destination node should send an acknowledgement to its one-hop neighbors when it receives a packet, since it does not further forward.

C. Application of the Dynamic Threshold Scheme

The dynamic threshold scheme is an iterative approach in which each node will filter requests by the dynamic uncertainty threshold and calculate the remaining utility. The utility R is then broadcast in the neighborhood. Nodes in the network should have a maximum possible transmission range. Therefore, each node can calculate the amount of energy c_{max} associated with the maximum possible communication range. Therefore, the normalized cost $\tilde{C}$ is: $\tilde{C} = c_i^j / c_{max}$. Expected gain G is the other important metric, which is the expected utility R_i in this model. T can be calculated using Formula 3.

Algo. 1 exploits the idea similar to Dijkstra's shortest path algorithm while using utility as the routing metric and applies the uncertainty mitigation scheme. All nodes except the destination will have the zero initial utility and the unselected status at the beginning. The algorithm works backward from the destination. A node will be marked as selected when it has the largest utility among all the unselected nodes and relax its neighbors. As shown in Fig. 2, node i, when relaxed by node j, calculates $(R_i)'$ and compares with the original R_i. If $(R_i)' > R_i$, then i calculates T according to Formula 3 and compares it with u_i^j. It then follows the rules below:

1) If $u_i^j > T$, reject. u is higher than acceptable.
2) If $u_i^j \leq T$, accept. $R_i \leftarrow (R_i)'$.

Although Algorithm 1 is centralized, a distributed implementation can be realized by using a back-off timer on

Algorithm 1 Dynamic Threshold

Initialize;
while s is not selected **do**
  Find node j with the largest R_j in the nodes with status unselected;
  Mark j as selected;
  For j's each neighbor i with status unselected, **Relax**(j, i);
end while

Relax(j, i)

Calculate utility: $(R_i)' = R_j \cdot p_i^j - c_i^j$;
Find the uncertainty threshold: $T = 1 - \tilde{C}^{\frac{G}{\lambda}}$;
if $(R_i)' \geq R_i$ and $u_i^j \leq T$ **then**
  Update $R_i \leftarrow (R_i)'$;
end if;

each node. The value of the back-off timer on each node is set to $(v - R_i)$, which reflects i's current utility. The distributed implementation can be gracefully integrated into reactive routing protocols, such as AODV or DSR.

Since the actual reliability in the network is highly dynamic and the observation results accumulate, the route discovery phase needs to be executed periodically. The route refresh period should be defined in the network's policy and the appropriate value for it is decided by the network's application. A smaller route refresh period leads to a more precise route selection while incurring larger route discovery costs.

VI. Analysis

We make some assumptions in this section to facilitate the analysis. 1) Nodes in the maximum transmission range of each other are considered to be in one-hop neighborhood. 2) Nodes can use adaptive power control when transmitting a package. 3) Nodes' actual reliability complies to the Bernoulli trial.

A. General Analysis

The uncertainty metric provides more information about the possible fluctuation in reliability estimation. Because the route discovery phase needs to be repeated periodically and the observation results accumulate, the selected best route may change. Path selection stability is a measure of the frequency of change in the selected path. The underlying reason for this change is the accumulating observations and the corresponding change in the estimated reliability metric.

Attribute 1: **(Selection Stability)**: The dynamic threshold scheme increases path selection stability.

As the evidence accumulates, the value of the estimated reliability stabilizes. If the variation is large enough, another route will become the best path under the given routing criterion, thereby causing changes in the selected path.

The dynamic threshold method will filter out nodes that are sensitive to changes in reliability before they are selected based on their high utility. Using the above setup, if node i is more sensitive to reliability changes and its uncertainty towards k is large enough in the beginning, it will be filtered out and the change in the selected path will not occur.

Attribute 2: **(Eventual Optimality)**: After accumulating enough observations, the utility-oriented routing mechanism using the proposed uncertainty mitigation scheme will achieve path selection optimality.

The observations are represented as (α, β). After a sufficiently long time, the number of observations increases to a large number, say $\alpha + \beta \rightarrow \infty$. Then the uncertainty metric $u_i^j \rightarrow 0$. For the dynamic threshold scheme, $u_i^j < T$ is always true because $T > 0$. In this scenario, no node will be filtered out. Therefore, Algo. 1's eventual optimality is equal to the optimality of the algorithm that selects a path with maximum utility. The proof of this optimality is in our previous work [1].

The uncertainty mitigation scheme has another favorable attribute which offers more flexibility to users. It reflects nodes' conservative or aggressive attitude by using the factor λ.

B. Simulation Evaluation

In our simulation, we compare the utility-oriented routing method with/without the uncertainty mitigation scheme. The routing algorithms include: (1) Optimal method, (2) Dynamic threshold scheme, and (3) MaxUtility [2] with our reliability estimation model. (3) is a special case of dynamic threshold in which a fixed estimated reliability is used without considering the uncertainty. The optimal method is the MaxUtility algorithm using the actual reliability.

All simulations are carried out on a customized simulator. We set up the simulation in a $900m \times 900m$ area. The actual stability of each link is randomly generated (uniform distribution) in the range $[0, 1]$. For each set of specified parameters, we run each algorithm 100 times and use the average value of the results to evaluate the performance. The packet value $v = 5000$. λ is uniform for the entire network to reflect the network's risk attitude with a default value of 0.5. Each node accumulates l observations before route discovery where l is a random number in $[0, 15]$.

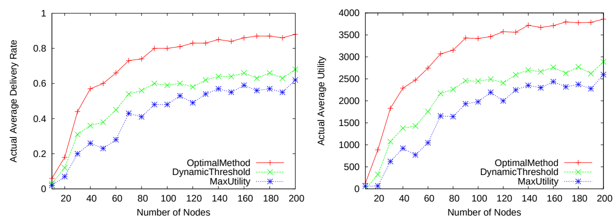
After all nodes in the network complete the accumulation of observations of their neighbors, the route discovery phase begins. Each algorithm selects the best path and 1000 packets are transmitted over each selected path for which the total cost, delivery ratio, and packet value are recorded.

C. Simulation Results

We adjust the number of nodes in the network to compare the performance of the different schemes. The number of nodes determines the node density, which in turn determines the communication cost and node degree.

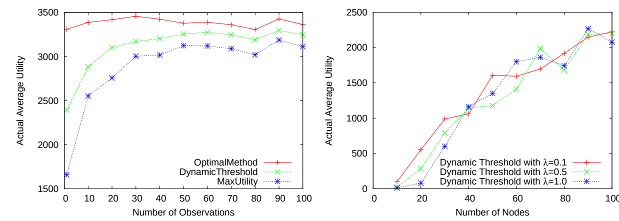
In Fig. 3(a), the delivery ratio of the optimal method is higher than the other two methods that use estimated reliability based on neighbor monitoring. The estimated reliability metric is inaccurate and contains uncertainty. Hence, there is a difference between the optimal path and the selected path for the other two algorithms. Because our scheme avoids nodes with high uncertainty, it achieves a better delivery ratio compared to MaxUtility. Fig. 3(b) shows the average utility. It is clear that our uncertainty mitigation scheme outperforms the MaxUtility algorithm, which omits uncertainty in the reliability evaluation.

Fig. 4(a) illustrates the change in average utility when observations accumulate. When more observations are accumulated, the estimation of the reliability metric becomes more accurate and tends to stabilize. Consequently, the uncertainty in estimation is reduced. Therefore, the differences between the optimal



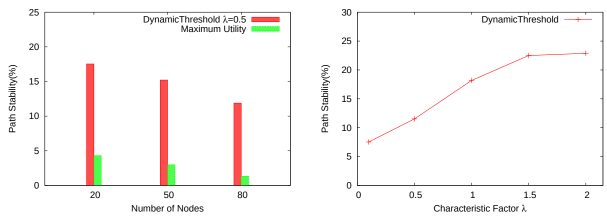
(a) Delivery ratio (b) Average utility

Fig. 3. Performance comparison.



(a) Number of observations l (b) Characteristic factor λ

Fig. 4. The effect of different parameters.



(a) Number of nodes n (b) Characteristic factor λ

Fig. 5. Path stability with different (a) n, and (b) λ.

method and the uncertainty mitigation scheme decrease when the number of observations before route discovery increases.

The results in Fig. 4(b) indicate that: using the same scheme, the answer as to whether $\lambda = 1.0$ or $\lambda = 0.1$ leads to better average utility is purely random. It implies that, although considering uncertainty helps us in making informed decisions, the answer as to 'whether the risk seeking or evading attitude is better' depends on the specific application domain.

Fig. 5(a) shows another advantage of our uncertainty mitigation scheme. In this simulation, we run the algorithms with a route refresh period of 30 observations. Using the uncertainty mitigation scheme, a great improvement in path stability can be seen, as uncertainty is considered beforehand.

Although the nodes' attitude cannot improve the average utility, it has a strong impact on path stability. From Fig. 5(b) we can see that the path stability increases as λ increases. When nodes are conservative, the paths are more stable.

The simulation results can be summarized as follows: 1) Using the uncertainty mitigation scheme can improve the delivery ratio and total utility. 2) The uncertainty mitigation scheme is especially useful when the number of observations are small. 3) The value of λ has no significant impact on utility improvement, however it does affect the path stability. 4) The uncertainty mitigation scheme increases path stability if the route discovery algorithm executes periodically.

VII. Related Work

Reliability is an important metric in wireless ad hoc networks [3]. Many routing algorithms [1] [2] [4] consider the reliability metric and compute their routing metrics on the basis of quantified reliability. Most of them assume a predetermined, fixed value for reliability. The method of collecting reliability information in a distributed manner and evaluating the inaccuracies and uncertainty in the collected value remains undiscussed. We develop and apply the uncertainty-centric reputation system in reliability estimation. This uncertainty-centric system is unique [5], as only a few of the existing reputation systems [6] [7] explicitly consider the uncertainty [8].

We use utility-oriented routing as a sample application in this paper. Other works also use utility as the optimization objective. A price-based scheme is presented in [9] to effectively allocate resources among multiple multi-hop flows. In [10], a market-based approach is proposed to efficiently allocate bandwidth. Our work [1] [2] combines reliability with link cost and designs an optimization model to maximize the expected utility. As the uncertainty mitigation scheme is logically compliant with the idea of utility, it can be applied to all of the existing utility-oriented routing algorithms.

VIII. Conclusion and Future Work

Evaluating and quantifying reliability is of critical importance in wireless ad hoc networks. Many existing optimization algorithms assume the availability of precise reliability information, which is unrealistic due to the dynamics of ad hoc networks. We present a novel reliability estimation model that accounts for uncertainty, and the uncertainty mitigation scheme. An extensive analysis and simulation study shows that the applicability of the reliability estimation model and the uncertainty mitigation scheme. In our future research, we plan to investigate opportunistic routing methods to reduce the path re-selection cost of our schemes.

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