A Cognitive Framework for Performance/Resilience Optimized Multipath Routing in Networks with Unstable Topologies

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***Abstract*-This paper proposes a framework for optimized multipath routing in a wireless network with frequently changing topology. The topology changes may be due to node mobility in mobile ad hoc networks, or limited node reliability and power supply in sensor networks. The framework attempts to minimize losses (regrets) resulted from uncertainty in the network state at the point of making the routing decision. This uncertainty results from delays in propagating rapidly changing network state information and high cost of network state updates in terms of the network resources. The framework yields the optimal route mixture in the neighborhood of the "best" route. This is consistent with observation [1] that while a desirable goal is to deliver data along the best available (primary) route, maintaining multiple routes through multipath may have beneficial effect on the network performance due to keeping track of the "best" route. The proposed framework explicitly accounts for this effect by assuming that the routing affects the level of uncertainty. Resiliency of the routing under uncertainty may be achieved by assuming that the uncertainty is adversarial, given the available information on the network state. This framework naturally allows for the game theoretic interpretation with routing algorithm making a feasible routing decision and adversarial environment selecting a feasible, i.e., consistent with available information, network state. The optimal route mixture is identified with (generally mixed) Nash routing strategy in the corresponding game. Future efforts should be directed towards solving the corresponding games.**

I. INTRODUCTION

Optimization of a routing algorithm in a wireless network is a challenging problem due to limitation on the available information on the network state at the point of making the routing decision. This uncertainty is a result of variations in the channel and load conditions on the one hand, and high cost of updating the network state information in terms of the network resources on the other hand. Channel conditions may change due to mobility in a mobile network, or limited node reliability and power supply in a sensor network. In the extreme case when no network state information is available, flooding or gossiping with completely random selection of the next hop (hops) is the only option [2]-[4]. However, downside of this approach is inefficient use of the resources (bandwidth and transmission power) in a case of flooding, or large delays in a case of a completely random gossiping. In another extreme case when complete information on the network state is available, shortest or minimum cost link state routing algorithm with appropriately defined link lengths (costs) results in a *single* optimal route [5]. In most practical situations, however, some limited information is available at the point of making the routing decision, and the challenge is finding a proper way to utilize this information to improve the network performance/resilience.

It is natural to expect that under this intermediate scenario the optimal routing algorithm uses multiple paths that concentrate in some neighborhood of the "optimal" route and this neighborhood grows as uncertainty in the network connectivity increases. Beneficial effects of splitting traffic among multiple feasible routes on network performance and resiliency have been known for quite some time. Dispersity Routing [6] improves network ability to transmit large files by combining resources of several routes. Recent results [7] demonstrated that traffic splitting may increase capacity of a mobile wireless network, however, at the cost of possibly very large delays. Numerous papers investigated resilience of the routing algorithm achieved by sending multiple copies of a packet over different routes. For applications to a wireless network see, for example, [8]. Most relevant for our purposes is observation [1] that while a desirable goal is to deliver data along the best available (primary) route, maintaining multiple routes through multipath routing may be beneficial for the network performance due to keeping track of the "best" route. The challenge, thus, is how to identify the optimal route mixture and, more generally, the optimal traffic split. The first problem has been empirically addressed in [1].

This paper proposes an analytical framework for route selection intended to balance performance and route maintenance capabilities of multipath routing. Resiliency of the routing under uncertainty is achieved by assuming that the uncertainty is adversarial, given the available information on the network state. This framework naturally allows for the game theoretic interpretation with routing algorithm making a feasible routing decision and adversarial environment selecting a feasible, i.e., consistent with available information, network state. The optimal traffic split is identified with (generally mixed) Nash routing strategy in the corresponding game. This optimal solution routes most of the traffic on the "optimal" path, but also sends some small portion of the traffic on non-optimal routes in some neighborhood of the "best" route for the purposes of route exploration and maintenance. Note that despite we assume source routing, the proposed framework can be also applied to optimization of a hop by hop routing.

We assume that the "best" route has minimum cost among all feasible routes where the link costs are some functions of possibly uncertain network state. We model uncertainty in the network state, directly, in terms of uncertain link costs, so that the "best" route may not be known to the source at the moment of making the routing decision. Usually, this formulation of uncertainty does not present any problem. For, example, in a wireless context networks are often modeled by a random graph with fixed set of nodes N where nodes $i \in N$ and $j \in N \setminus i$ are directly connected by a link $l = (i, j)$ with some probability p_l and not directly connected with probability $q_l = 1 - p_l$ [8]. Direct connectivity for different pairs of nodes are jointly statistically independent. Under these assumptions the probability that route r exists is the product of the probabilities of existence of all the links on this route:

$$p_r = \prod_{l \in r} p_l \tag{1}$$

The problem of finding the most reliable path within the set of feasible routes for a given origin-destination R is formulated as follows:

$$r^{opt} = \arg\max_{r \in R} p_r \tag{2}$$

and can be interpreted as finding the shortest (minimum cost) path

$$r^{opt} = \arg\min_{r \in R} \sum_{l \in r} w_l \tag{3}$$

with respect to the link weights (costs or lengths)

$$w_l = -\log p_l \tag{4}$$

Except for the case of equal cost multipath, minimum cost routing (3) results in a single optimal route. In a case of equal minimum cost multipath, routing (3) does not identify the optimal traffic split among minimum cost feasible routes.

Depending on the specific problem, the link cost may also represent power, or QoS required for transmission on the link, or combination of both. In practice, since link weights are not known precisely, they are replaced with point estimates $w_l \approx \widetilde{w}_l$, and the optimal route is determined based on these estimates:

$$\widetilde{r}^{opt} = \arg\min_{r \in F} \sum_{l \in r} \widetilde{w}_r \,. \tag{5}$$

In a particular case of finding the most reliable path (2) $\widetilde{w}_l = -\log \widetilde{p}_l$, where the point estimate for the probability of link l connectivity is $\widetilde{p}_l$. The result of this procedure is again a single "optimal" path, usually, very sensitive to point estimates for the link weights.

However, despite the link weights w_l may be constant during a packet transmission, the numerical values of w_l usually are not known precisely. In a case of pro-active routing the rate of change in the link path losses due to mobility may become comparable with rate of updates in the routing information. In a case of on-demand routing short exploratory packets relay almost instantaneous information on the link path losses, but due to the fast fading and limited number of "observations", the link conditions faced by the consequent payload transmissions are likely to be different. Situation becomes even worse for delay sensitive applications, which are likely to require connection oriented services. Setting up a connection for sending a stream of packets increases uncertainty in the propagation conditions faced by packets as duration of the connection increases.

The paper is organized as follows. Section II discusses models of uncertainty in the link costs. Section III describes game theoretic framework for optimized multipath routing. Section IV solves the corresponding game in a case of two feasible routes and discusses some implications of route stability on the routing decisions. Finally, conclusion briefly summarizes results and outlines directions of future research.

II. Uncertain Link Costs

We assume that information on a link l weight w_l available to a source s can be quantified in terms of the set of probability distributions

$$q_l(w|\lambda_l, \theta_l) = \Pr(w_l \le w|\lambda_l, \theta_l) \tag{6}$$

where the rate of source s transmission over link l is λ_l. In practice, distribution (6) is determined from observations. We assume that the form of the distribution $q_l(w|\lambda_l, \theta_l)$ is known. Vector $\theta_l \in \Theta_l$ characterizes parameters of this distribution, usually the distribution moments, to be estimated from the measurements. Fixed set Θ_l represents the "confidence" region for the vector θ_l. For simplicity we assume that weights of different links are jointly statistically independent:

$$Q = \prod_l q_l(w_l|\lambda_l, \theta_l) \tag{7}$$

Modeling uncertainty in the link weights by assuming that link weights are random variables with some known probability distributions has been proposed in [9]. This framework results in the single "best" route that has the minimum average cost. Since in practice the distributions and average link costs are the result of statistical inferences based on historical data, papers [10]-[11] have proposed to explicitly incorporate uncertainty in these distributions by introducing parameters $\theta_l \in \Theta_l$. This paper takes the model of uncertainty in the link costs a step further by assuming that distribution (6) depends on the transmission rate λ_l. Due to limited space we do not describe formal properties of the distribution (6) as a function of λ_l in a general case. Note only, that it is natural to assume that increase in λ_l reduces uncertainty in the distribution (6).

In the rest of this section we illustrate our model for a particular case of "hard" constraints on the link weights

$$w_l \in [\breve{w}_l, \widehat{w}_l] \tag{8}$$

It is natural to assume that given point estimate for the link weight $\widetilde{w}_l$, the low boundary $\breve{w}_l = \breve{w}_l(\lambda)$ is a non-decreasing, and the upper boundary $\widehat{w}_l = \widehat{w}_l(\lambda)$ is a non-increasing function of the rate λ, and

$$\lim_{\lambda\to\infty} \breve{w}_l(\lambda) = \lim_{\lambda\to\infty} \widehat{w}_l(\lambda) = \widetilde{w}_l \quad (9)$$

It is easy to see that model of uncertain link weights (8) fits into general model (6). The "width" of the confidence intervals (8)

$$\delta_l = \widehat{w}_l - \breve{w}_l \quad (10)$$

represents uncertainty in the available information on the current network state, and is related to the "confidence" in the reliability of this information. In a particular case of finding the most reliable path (2)-(3) the bounds in (8) are

$$\breve{w}_l = -\log \breve{p}_l,\ \widehat{w}_l = -\log \widehat{p}_l, \quad (11)$$

where the available information on the link connectivity p_l is quantified in terms of the confidence interval

$$p_l \in [\breve{p}_l, \widehat{p}_l] \quad (12)$$

Model (8) allows for various interpretations. One interpretation could be setting up a path for a flow in a connection-oriented mode for a streaming, e.g., video application. Assuming that the link weights $w_l = w_l(t)$ at the moment t of making the routing decision are known, the point projection for the link weights $w_l = w_l(t+\tau)$ to the lifetime of the connection (flow) $[t, t+\tau]$ is $\widetilde{w}_l = \widetilde{w}_l(t+\tau)$. The low and upper boundaries of the confidence interval for the link weight projection are $\breve{w}_l = \breve{w}_l(t+\tau)$ and $\widehat{w}_l = \widehat{w}_l(t+\tau)$ respectively. This situation is illustrated in Figure 1.

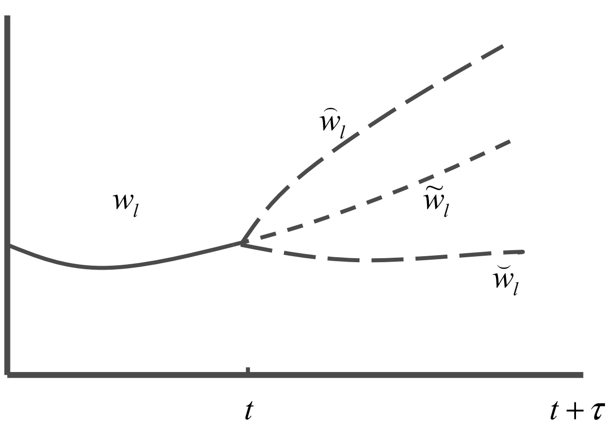

Figure 1. Uncertainty as a function of time horizon τ.

If uncertainty (8) is a result of finite frequency of updates of the network state information and delays in disseminating this information, then the confidence interval (8) widens with time τ elapsed from the last update. Briefly illustrate this point on an example of mobile ad hoc network where mobile m has maximum speed $v_m^{\max}$, and the routing attempts to minimize the transmission power. On a flat surface the power needed to transmit on a link $l = (i, j)$ is a function of the physical length of this link: $w_l = f_l(\lambda_l, d_l)$. Assuming that the maximum speed of mobile m is $v_m^{\max}$, the uncertainty in the link $l = (i, j)$ physical length is

$$d_l \in [\breve{d}_l, \widehat{d}_l] \quad (13)$$

where

$$\breve{d}_l = \max\{0,, \widetilde{d}_l - (v_i^{\max} + v_j^{\max})\tau\},$$

$$\widehat{d}_l = \widetilde{d}_l + (v_i^{\max} + v_j^{\max})\tau,$$

the last observed length of the link l is $\widetilde{d}_l$, and time elapsed from this last update is τ. Figure 2 illustrates uncertainty (13).

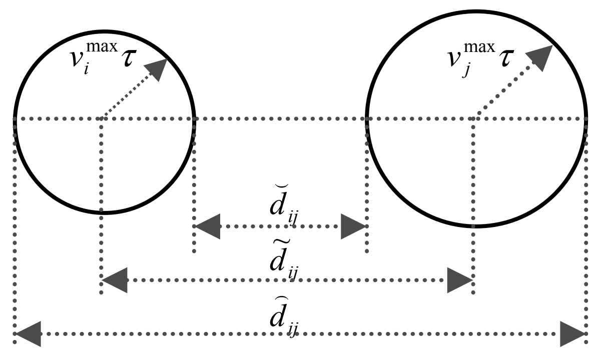

Figure 2. Uncertainty in the distance between nodes i and j.

This uncertainty in the physical link lengths translates into uncertainty in the link costs (8), where $\breve{w}_l = f_l(\lambda_l, \breve{d}_l)$, $\widehat{w}_l = f_l(\lambda_l, \widehat{d}_l)$. Figure 3 illustrates difficulty of determining the best route from node 1 to node 2 in a case of four-node mobile network with uncertain node locations due to the mobility.

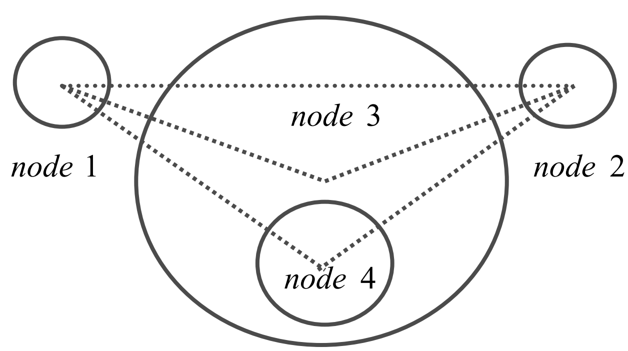

Figure 3. Which route is better r_{12}, r_{132}, or r_{142}?

Circles in the figure 3 represent possible locations of the corresponding nodes. There are three possible routes: direct route $r_{12} = 1 \to 2$, and two two-hop routes $r_{132} = (1 \to 3 \to 2)$ and $r_{142} = (1 \to 4 \to 2)$. It is easy to see that the best route may be very sensitive to uncertain node locations. Conventional approach assumes some fixed probability distribution for the node locations, and bases the routing decision on the corresponding average route costs. However, this approach does not resolve the sensitivity problem since the average route costs and the resulting best route remain very sensitive to selection of the corresponding distributions. Also, this essentially Bayesian approach results in the single "best" route, and thus does not characterize the beneficial route maintenance effect of multipath routing. A simple model for describing this effect can be obtained by assuming that time elapsed from this update is

$$\tau_l = \vartheta_l + \frac{1}{\lambda_l + \mu_l} \tag{14}$$

where the frequency of updating information on the link l due to pro-active nature of the routing protocol is μ_l, packet data rate through link l is link λ_l, and the delay in receiving this information at the source is ϑ_l. Despite formula (14) may be oversimplification for quantitative conclusions, qualitatively it captures the "uncertainty reducing property" of the multipath routing. It is easy to see that an attempt to combine this property with Bayesian routing decision results in unstable routing.

III. Optimized Multipath Routing

The average cost of a link l with respect to distribution (6) is a function of the parameter θ_l and data packet rate through this link λ_l:

$$w_l^{ave}(\theta_l, \lambda_l) = E_q[w_l] \tag{15}$$

The average cost of a route is a function of vectors $\theta_r = (\theta_l : l \in r)$ and $\lambda_r = (\lambda_l : l \in r)$:

$$w_r^{ave}(\theta_r, \lambda_r) = \sum_{l \in r} w_l^{ave}(\theta_l, \lambda_l) \tag{16}$$

and thus the optimal, with respect to the average cost, route

$$r^*(\theta, \lambda) = \arg\min_{r \in F} \sum_{l \in r} w_r^{ave}(\theta_r, \lambda_r) \tag{17}$$

depends on vectors $\theta = (\theta_l : l \in r \subseteq F)$ and $\lambda = (\lambda_l : l \in r \subseteq F)$.

If traffic generated by a source s to some given destination is split among feasible routes F, then the transmission rate over link l from source s is

$$\lambda_l = \lambda_s \sum_{r: l \in r} \gamma_r \tag{18}$$

where the total traffic generated by source s is λ_s, the portion of this traffic carried on route $r \in F$ is γ_r, and

$$\sum_{r \in F} \gamma_r = 1, \; \gamma_r \geq 0 \tag{19}$$

The average expected route cost resulted from traffic split $\gamma = (\gamma_r)$ is

$$\overline{w}^{ave}(\theta, \gamma) = \sum_{r \in F} \gamma_r w_r^{ave}[\theta_r, \lambda_r(\gamma)] \tag{20}$$

where $\lambda_r(\gamma) = (\lambda_l(\gamma) : l \in r)$, and $\lambda_l(\gamma)$ is given by ( ).

It is natural to define the optimal traffic split $\gamma = (\gamma_r)$ by minimizing the expected route cost (20):

$$\gamma^*(\theta) = \arg\min_{\gamma} \overline{w}^{ave}(\theta, \gamma) \tag{21}$$

Given $\theta \in \Theta$, the optimal routing (21) splits traffic among routes with minimum cost (equal cost multipath) [5]. The problem is that the optimal split (21) depends on the unknown vector $\theta \in \Theta$, and optimization problem (21) is typically ill-posed. Conventional approach to solving ill-conditioned problems is regularization by imposing additional conditions on the solution [11]-[12]. Additional condition of robustness with respect to unknown vector $\theta \in \Theta$ leads to the following game theoretic framework for optimized multipath routing.

Consider a game of the routing algorithm selecting traffic split $\gamma = (\gamma_r)$ in an attempt to minimize the route cost (20) and the adversarial uncertainty selecting vector $\theta \in \Theta$ in an attempt to obstruct these efforts. It is natural to define adversarial intent as an attempt to maximize the expected regret (loss)

$$\overline{L}(\theta, \gamma) = \sum_{r \in F} \gamma_r L(w^{ave}, r) \tag{22}$$

where the regret (loss) function is [13]

$$L(w, r) = w_r^{ave} - \min_{r' \in F} w_{r'}^{ave} \tag{23}$$

and vector $w^{ave} = (w_r^{ave})$ is given by (15)-(16). It can be shown that under certain weak assumptions the optimal solution to this game can be obtained by solving the following optimization problem

$$\overline{L}(\theta^*, \gamma^*) = \min_{\gamma} \max_{\theta} L(\theta, \gamma) \tag{24}$$

subject to the corresponding constraints. Optimization problem (24) can be solved by fixed point equations as follows.

Fix the traffic split is $\gamma = (\gamma_r)$, and consider a zero sum game G of the routing algorithm choosing feasible route $r \in F$ in an attempt to minimize loss (23) and adversarial uncertainty choosing $\theta \in \Theta$ in an attempt to maximize loss (23). Let (generally mixed) Nash routing solution to this game select feasible route $r \in F$ with probability α_r. Vector $\alpha = (\alpha_r)$ is a function of fixed vector $\gamma = (\gamma_r)$: $\alpha = \varphi(\gamma)$. Consider fixed point equations

$$\gamma = \varphi(\gamma) \tag{25}$$

It is easy to see that solution to the optimization problem (24) also solves fixed point equations (25). Due to limited space we do not consider stability of (25).

We conclude this section with the following remarks. First, game G can be reduced to a finite game by eliminating dominated strategies for the adversarial environment [14], [11]. Second, the optimal route mixture α only includes routes of minimum cost (equal cost multipath), and thus is equivalent to the route optimality principle in load balancing [15]. This relation between guarding against adversarial uncertainty and load balancing deserves further investigation. Finally, randomized routing α has interesting interpretation as the shortest random walk in adversarial environment [15].

IV. EXAMPLE: A CASE OF TWO FEASIBLE ROUTES

In this section we illustrate the proposed framework on an example of two feasible routes r_1 and r_2 assuming hard constraints on the link weights (8). Since we need to consider only non-overlapping links of the routes r_1 and r_2 introduce corresponding lower and upper bounds for the weights of non-overlapping parts of routes r_i, $i = 1,2$:

$$\breve{w}_i = \sum_{l \in r_i \setminus r_{12}} \breve{w}_l , \tag{26}$$

$$\hat{w}_i = \sum_{l \in r_i \setminus r_{12}} \hat{w}_l , \tag{27}$$

where $r_{12} = r_1 \bigcap r_2$. It is easy to see that if intervals $[\breve{w}_1, \hat{w}_1]$ and $[\breve{w}_2, \hat{w}_2]$ do not overlap with each other:

$$[\breve{w}_1, \hat{w}_1] \bigcap [\breve{w}_2, \hat{w}_2] = \varnothing , \tag{28}$$

the game has solution in pure strategies, and the optimal route is

$$r_* = \begin{cases} r_1 & if \quad \hat{w}_1 < \breve{w}_2 \\ r_2 & if \quad \hat{w}_2 < \breve{w}_1 \end{cases} \tag{29}$$

If intervals $[\breve{w}_1, \hat{w}_1]$ and $[\breve{w}_2, \hat{w}_2]$ do overlap with each other:

$$[\breve{w}_1, \hat{w}_1] \bigcap [\breve{w}_2, \hat{w}_2] \neq \varnothing , \tag{30}$$

the game has solution in mixed strategies. It can be shown that all feasible strategies for the adversarial environment are dominated by the following two strategies:

$$s_1 = \{(w_l = \breve{w}_l, \forall l \in r_1 \setminus r_{12}) \,\&\, (w_l = \hat{w}_l, \forall l \in r_2 \setminus r_{12})\}$$

$$s_2 = \{(w_l = \hat{w}_l, \forall l \in r_1 \setminus r_{12}) \,\&\, (w_l = \breve{w}_l, \forall l \in r_2 \setminus r_{12})\}$$

The payoff matrix in the corresponding 2×2 game is

$$\begin{array}{ccc} & r = r_1 & r = r_2 \\ s = s_1 & 0 & \hat{w}_1 - \breve{w}_2 \\ s = s_2 & \hat{w}_2 - \breve{w}_1 & 0 \end{array} \tag{31}$$

The optimal routing strategy is to select route r_1 with probability

$$\alpha_1 = \frac{1}{2}\left(1 + \frac{\tilde{w}_2 - \tilde{w}_1}{\delta_1 + \delta_2}\right) \tag{32}$$

and select route r_2 with probability $\alpha_2 = 1 - \alpha_1$, where

$$\tilde{w}_i = \frac{\hat{w}_i + \breve{w}_i}{2} \tag{33}$$

and

$$\delta_i = \frac{\hat{w}_i - \breve{w}_i}{2} \tag{34}$$

Note that in general, equal traffic split is not optimal. The optimal strategy for the adversarial environment is to select strategy $s = s_1$ with probability $\beta_1 = \alpha_2$, and to select strategy $s = s_2$ with probability $\beta_2 = \alpha_1$, where α_i, $i = 1,2$ are given by (32). It is easy to verify that for this optimal mixed strategy, routes r_1 and r_2 have the same average weights: $\overline{w}_1^* = \overline{w}_2^*$, and thus the optimality principle of splitting traffic only among minimum cost routes is preserved.

To demonstrate the role of route stability on the optimal routing decision, consider selection of the most reliable route under uncertain connectivity (3), (11)-(12). In this case

$$\tilde{w}_i = -\frac{\log \hat{p}_i + \log \breve{p}_i}{2} \tag{35}$$

and

$$\delta_i = -\frac{\log \hat{p}_i - \log \breve{p}_i}{2} \tag{36}$$

where "confidence region for the corresponding connectivity probability p_i is $\breve{p}_i \le p_i \le \hat{p}_i$, and the point estimate for p_i is $\tilde{p}_i = (\hat{p}_i + \breve{p}_i)/2$. It is easy to see that increase in the route r_i instability reduces the optimal portion of traffic α_i allocated to this route. In particular, the traffic should be split equally between routes r_1 and r_2, i.e., $\alpha_1 = \alpha_2$ if

$$\breve{p}_1 \hat{p}_1 = \breve{p}_2 \hat{p}_2 \tag{37}$$

A case of extremely unstable route r_1 with $\breve{p}_1 = \max\{0,\ 2\tilde{p}_1 - 1\}$, $\hat{p}_1 = \min\{1,\ 2\tilde{p}_1\}$, and completely stable route r_2 with $\breve{p}_2 = \hat{p}_2 = \tilde{p}_2$ is shown in Figure 4. In the region OABFO the entire load should be carried on the route r_2. In the region FCDF the entire load should be carried on the route r_1. In the region FBCF traffic should be split between routes r_1 and r_2, i.e., $\alpha_1, \alpha_2 > 0$.

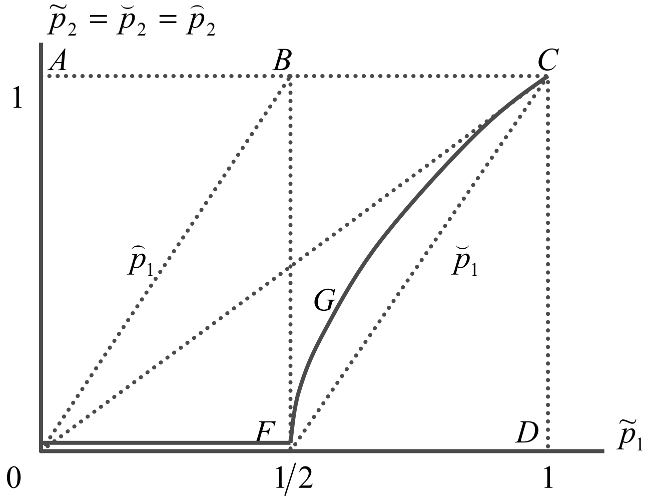

Figure 4. Optimal traffic split between completely unstable route r_1 and completely stable route r_2.

The traffic should be split equally between routes r_1 and r_2, i.e., $\alpha_1 = \alpha_2$ on the curve OFGC described by equation

$$\tilde{p}_2 = \begin{cases} \varepsilon & if \quad \tilde{p}_1 \le 1/2 \\ \sqrt{2\tilde{p}_1 - 1} & if \quad \tilde{p}_1 > 1/2 \end{cases} \tag{38}$$

where $\varepsilon > 0$ is some arbitrarily small constant.

Finally, briefly demonstrate the interplay between route cost miinimization and reduction in uncertainty. Assuming that acknowledgments of the successful packet delivery is the only source of information on the network state, model (14) yields

$$\delta_i = \chi_i / \alpha_i \tag{39}$$

where χ_i are some parameters describing level of uncertainty for route r_i. Combing (39) with (32) we obtain fixed point equation for the optimal traffic split $\alpha = (\alpha_1, \alpha_2)$. Due to limited space we only note that in a case of small uncertainties $\delta_i \to 0$, the most of the traffic should be carried on the route with minimum expected cost $\tilde{w}_i$, $i = 1,2$. In a case of "large" uncertainty for both routes, traffic should be split equally between routes: $\alpha_1 = \alpha_2 = 1/2$.

V. Conclusion

This paper has proposed a framework for optimized multipath routing in a network with frequently changing topology. The framework attempts to find the optimal operating points balancing performance and route discovery capabilities of multipath routing. Future efforts should be directed towards developing approximate solutions for the corresponding games under various scenarios for the adversarial environment. (For some partial results see [12], [15]-[16].) A Bayesian game model, allowing the routing algorithm to adapt to the uncertain environment, appears to be a natural extension of the proposed framework. However, success of such extension will depend on overcoming computational difficulties of solving the corresponding Bayesian games.

High dimension, inherent uncertainties, and limited resources in wireless network suggest broader view of selecting routes as a cognitive process of adaptation and competition. Randomization of the routing decisions can be viewed as mutations intended to adapt to changing conditions influencing the route costs. As a result of interference, different sources share, and thus compete for the same resources, e.g., transmission power and bandwidth. This process appears to be similar to adaptation and competition in natural selection. Exploring analogies between routing and evolutionary algorithms may lead to highly adaptive, efficient and resilient network management schemes.

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