Truthful Least-Priced-Path Routing in Opportunistic Spectrum Access Networks

Tao Shu and Marwan Krunz
Department of Electrical and Computer Engineering
The University of Arizona

***Abstract*—We study the problem of finding the least-priced path (LPP) between a source and a destination in opportunistic spectrum access (OSA) networks. This problem is motivated by economic considerations, whereby spectrum opportunities are *sold/leased* to secondary radios (SRs). This incurs a communication cost, e.g., for traffic relaying. As the beneficiary of these services, the end user must compensate the service-providing SRs for their spectrum cost. To give an incentive (i.e., profit) for SRs to report their true cost, typically the payment to a SR should be higher than the actual cost. However, from an end user's perspective, unnecessary overpayment should be avoided. So we are interested in the optimal route selection and payment determination mechanism that minimizes the price tag of the selected route and at the same time guarantees truthful cost reports from SRs. This setup is in contrast to the conventional truthful least-cost path (LCP) problem, where the interest is to find the minimum-cost route. The LPP problem is investigated with and without capacity constraints at individual SRs. For both cases, our algorithmic solutions can be executed in polynomial time. The effectiveness of our algorithms in terms of price saving is verified through extensive simulations.**

I. Introduction

By far spectrum is the most critical resource in wireless communications. Recently, it was revealed that under the current fixed-spectrum-allocation paradigm, portions of the allocated spectrum are significantly underutilized. This finding motivated extensive research on *opportunistic spectrum access* (OSA) [19], the premise of which is to allow for secondary re-use of the spectrum to improve its utilization. Under OSA, a secondary radio (SR) is allowed access to a channel that is not currently being used by the primary radios (PRs) of the channel, given that such a opportunistic access does not intervene with PRs' normal communications.

Inevitably, economic considerations are critical driving forces behind the realization of OSA. Under the assumption of economically rational players, a primary owner of the spectrum has interest in opening its idle spectrum for secondary re-use only if such action is profitable. As a result, the acquisition and access of the spectrum by SRs incur a certain cost, which generally takes the form of monetary payment made to the primary owner of the spectrum. Such an economic consideration has been reflected in recent studies on OSA. For example, spectrum auction works in [21] and [8] considered the situation where SRs acquire spectrum through a bidding process. The spectrum-leasing architecture studied in [12] requires SRs to subscribe to (and pay for) the spectrum-status information broadcasted by a spectrum server. In addition, the current IEEE 802.22 WRAN standard is based on an infrastructure-type architecture, which by design is suitable and intended for implementing fee-based services for SRs.

In contrast to existing works that study the cost aspects of acquiring spectrum, in this paper we study its "end system" perspective, focusing on the implication of such a cost. We limit our interest to the economical aspects of the routing problem under OSA. Specifically, we consider a situation where a source SR wishes to purchase a route to some destination. Intermediate SRs along this route relay the traffic from this source, until it finally reaches its destination. Such traffic relaying is not free for the source, since intermediate SRs must have paid to access their channels (and thus are able to provide relay service for the source). They do not have the incentive to relay the traffic unless the source compensates them for their spectrum cost. The problem for the source is to decide the cheapest route, i.e., its total payment to the relaying nodes (equivalently, the price of the route) is the minimum among all feasible routes from the source to the destination. We refer to this problem as the least-priced-path (LPP) problem. Note that even though we assume the source pays for the route, the problem does not lose its generality when the destination makes the payment.

At a first glance, the LPP problem is seemingly trivial and can be solved by the following naive method. The source would ask all SRs to report their costs. The source would then choose the shortest path to the destination with the reported cost used as a node's weight. Each SR along the selected path would be paid with the equivalent amount of its reported cost. The problem with this method is that intermediate SRs may exaggerate their claimed costs for the purpose of getting higher profits (in here, profit is defined as the difference between the payment a SR receives and its true spectrum cost). This is especially true when the intermediate SR belongs to a different administrative domain than the source, and thus is opt to act selfishly to maximize its own interests. As a result, the source could end up paying an unnecessarily high price for the route it chooses.

The above selfish behavior has been well addressed in the literature under a different setup, namely, finding the least-cost path (LCP) (e.g., see [11], [7], [6], [16]). The basic idea in the LCP algorithm is to design a *truthful* payment mechanism that guarantees that cheating in the claimed cost cannot increase the relaying node's profit. As a result, such a node has no incentive to exaggerate its true cost. The LCP can be subsequently constructed based on the reported costs, since they are guaranteed by the payment mechanism to be the true ones.

In contrast to the LCP problem, the LPP problem studied in this paper takes into account the following three new aspects presented by the OSA paradigm. First, instead of minimizing the *cost* of the route, we aim at minimizing the *price* of the route. This is more attractive to an end user, because price is the actual expense the end user has to pay. As will become clear shortly, under the truthfulness requirement, there is no straightforward conversion between these two objectives, and a new formulation is required for the LPP problem.

Second, in contrast to all existing LCP formulations, where the cost of a node is a constant, here cost is modeled as a random variable. The node cost in OSA represents the monetary rate the SR node has to pay in order to acquire the spectrum. Such a rate changes with the supply-demand dynamics of the available spectrum in the vicinity of the node. When the supply-demand is tight, a SR will have to pay more in order to access the spectrum. Likewise, the cost drops when more idle spectrum becomes available for secondary re-use. In line with this randomized node cost, we are interested in finding a randomized routing strategy, which can adapt to the dynamics of the node cost, with the goal of minimizing the expected price of the route.

Third, when constructing a route, we consider the capacity limit of each node. Being restricted to a secondary role, a SR cannot guarantee it can always acquire the amount of spectrum it needs. Therefore, an end-to-end flow may have to be split into multiple sub-flows in order to be accommodated by the capacity-limited intermediate nodes, leading to multi-path routing. This is in contrast to the single-path situation considered in the LCP problem, where no capacity constraint is imposed on relaying nodes.

In this paper, we model truthful LPP routing as a mechanism design problem. Our investigation is divided into two parts. In the first part, we find the LPP without imposing a node-capacity constraint. This simplified formulation applies to the scenario where the rate demand is relatively low, such that intermediate nodes can always support it. In the second part, we consider the problem with a given source rate demand and given capacity constraints at intermediate nodes. Our work can be considered as an extension to the Myerson's optimal auction theory [10], whereby the bidders in the Myerson's auction problem correspond to paths in the LPP formulation. The major difference is that in Myerson's problem, the bidders are independent individuals. No matter how a bidder changes its bid, it cannot change other bidders' bids. However, in our LPP problem, paths need not be node-disjoint. As a result, when a node that is shared by multiple paths changes its claimed cost, the claimed cost of all involved paths will also be changed. In other words, the players in our problem are no longer independent. Therefore, the results in Myerson's work cannot be directly applied to our problem.

The remainder of this paper is organized as follows. We review the related work in Section II. We formulate the LPP problem in Section III. The problem is addressed without and with a node-capacity constraint in Sections IV and V, respectively. Simulation results are presented in Section VI. We conclude our work in Section VII.

II. Related Works

Reference [5] is probably the most relevant work to the first part of our work, i.e., LPP without a node capacity constraint. In [5], the authors studied the minimization of the expected price of a *single path*. Our results in Section IV is compatible with theirs. The major difference is that, by definition, their optimization targets only single-path routes, but our formulation starts from a more general setting that allows for multi-path routing. This change in formulation is nontrivial, because now we need to explicitly account for the inter-dependence between paths. We then rigidly prove that in the absence of capacity constraints, the LPP route only contains a single path. Our major contribution is to prove that the algorithm under development is not only optimal among the set of single paths, but also optimal among all possible combinations of paths. As to the second part of our work, i.e., LPP with a node capacity constraint, to the best of our knowledge, ours is the first that formulates and addresses this problem.

Aside from [5], other related works on truthful routing have focused on the LCP problem. This problem was first introduced by Nisan and Ronen in their seminal paper [11], where they solved the truthful unicast LCP routing by applying the celebrated VCG mechanism. In [11], the cost of an agent (a node or an edge) is used as the agent's weight in the graph. The LCP is the shortest path from the source to the destination. The payment p^e to an agent e is 0 if e is not in the LCP and $p^e = d_{G|e=\infty} - d_{G|e=0}$ if it is. Here $d_{G|e=\infty}$ is the length of the shortest path that does not contain agent e, and $d_{G|e=0}$ is the length of the shortest path when the cost of e is zero.

Several follow-up works extended the basic VCG algorithm [11] into various networking environments. This includes the ad hoc-VCG in [1], the VCG-based BGP (Border Gateway Protocol) in [6], the multicast version of VCG in [17], and more recently for opportunistic routing [18]. The work in [9] formulated the multi-path LCP problem but did not provide a solution. The work in [14] gave initial results for this problem by only considering the special case that all paths in the graph are disjoint. Some works, e.g., [7], focused on the complexity issues of the VCG payment calculation. Other works, e.g., [20][15][16], went beyond the routing layer and encompassed a cross-layer methodology in studying the LCP problem.

The high overpayment issue in VCG-based LCP routing was first noticed by Archer and Tardos [2]. They investigated the *frugal path* problem (FPP), which aims at designing a mechanism that selects a path and induces truthful cost revelation, but without paying high price. The authors in [2] showed that no reasonable mechanism can always avoid paying a high premium to induce truthtelling. Subsequent works on FPP, e.g., [6] [4], focused on characterizing the bounds on the price of general truthful routing mechanisms. Rather than studying the bounds, the LPP problem in this paper differs from FPP in that it explicitly minimizes the price of the route in a given graph.

III. System Model and Problem Formulation

A. Preliminaries

The LPP problem is well suited for analysis by means of *mechanism design*, a branch of game theory. First, we briefly review a few definitions and concepts from mechanism design. We then describe our model and formulate the problem using a mechanism design's terminology.

A mechanism design problem considers a game of n *agents*, each with its own strategy set. For each agent i, $1 \leq i \leq n$, there is some private information t_i (only known to agent i), called its *type*. We consider the *direct revelation* strategy set in this study, i.e., agents simultaneously report their types to the mechanism. Denote the reported type of agent i by $\tilde{t}_i$ (this may not be the same as the true type t_i) and the vector of reported types from all agents as $\tilde{t} = (\tilde{t}_1, \ldots, \tilde{t}_n)$. The mechanism takes $\tilde{t}$ as input, and computes an output $X(\tilde{t})$ and a payment to agents $p(\tilde{t}) = (p_1(\tilde{t}), \ldots, p_n(\tilde{t}))$. Given the output X and the type t_i, agent i's *valuation* is decided by a real-valued function $v_i(t_i, X)$. Accordingly, agent i's profit for reporting $\tilde{t}_i$ is given by $u_i \stackrel{\text{def}}{=} p_i(\tilde{t}) - v_i(t_i, X)$. An agent is defined as being rational if it always reports a $\tilde{t}_i$ that maximizes its profit.

The main task of a mechanism design problem is to design the functions $X(\tilde{t})$ and $p(\tilde{t})$ that maximize some social interests (e.g., social welfare) of the game. Usually the following properties are desired in the mechanism:

1) Incentive compatible (IC): A mechanism is IC if each rational agent maximizes its profit by reporting its true type t_i.
2) Individual rational (IR): A mechanism is IR if each agent's profit for participating in the game is nonnegative.

When a mechanism is both IC and IR, we say it is truthful (or equivalently, strategy-proof).

B. Network Model and Problem Formulation

We consider an OSA network whose topology is defined by a directional graph $G = (V, E)$, where V and E are the set of SR nodes and the set of directional links between SRs, respectively. Each node j in V can access a certain amount of spectrum, say b_j, by paying a cost c_j to the primary spectrum owner for each packet it transmits over the spectrum. This cost is due to, for example, a winning bid in a spectrum auction or an agreed-upon rent in a spectrum lease, and thus is considered private information (i.e., the type) only known to node j. Because this cost depends on the supply-demand dynamics of available spectrum around node j, c_j is modeled as a random variable. Here we stick to the conventional economics approach of Bayesian optimal mechanism design by assuming that the probability density function (p.d.f.) of c_j, denoted by f_j, is known to the mechanism. Let the domain of f_j be $D_j \stackrel{\text{def}}{=} [v_j, w_j]$, where $v_j \geq 0$, $w_j \geq 0$, and $v_j \leq w_j$. In practice, for a truthful mechanism, f_j and D_j can be pragmatically constructed based on historical reports of the cost c_j. In our analysis, we assume perfect knowledge of f_j, but we relax this condition in our simulations to study the sensitivity issue of our algorithm. We assume that c_j does not change during a session, but may change from one session to another. Here, a session represents the continuous transmission of a burst of packets. For two nodes j and k, f_j and f_k are independent but not necessarily identical. This assumption captures the basic fact that in an OSA system, different nodes may experience heterogeneous spectrum availabilities, and thus their costs are stochastically non-identical. We also assume that the interference issue has been taken care of by the spectrum allocation mechanism employed in the network, so that interfering nodes operate over different channels. This assumption is true for nearly all spectrum auction and leasing mechanisms, e.g., the algorithm in [21] takes as input the interference graph to avoid selling a channel to two nodes that interfere with each other. We also assume that even though a node is only allowed to transmit over channels it has acquired, it can tune to any channel for reception.

Now consider a traffic flow that originates from a source node s and terminates at destination node d. The flow lasts for multiple sessions. Let $n \stackrel{\text{def}}{=} |V - \{s, d\}|$ ($|.|$ is the cardinality of a set), $m \stackrel{\text{def}}{=} |E|$, and label the nodes in $V - \{s, d\}$ as $j = 1, \ldots, n$. Let the set of all paths from s to d be $\mathbf{R}_{sd}$. Let $N \stackrel{\text{def}}{=} |\mathbf{R}_{sd}|$. Note that the enumeration of paths from s to d is only required for the problem formulation. Our final algorithms do not have such a requirement. The routing mechanism operates on a session-by-session basis. At the beginning of a session, each node j in V reports its cost to the routing mechanism as $\tilde{c}_j$. A truthful mechanism should guarantee that each node reports its true cost $\tilde{c}_j = c_j$, i.e., the mechanism must satisfy the IC and IR constraints. We will formulate these constraints after we finish describing the general operation of the mechanism.

The mechanism takes as input the costs $c = (c_1, \ldots, c_n)$ from the nodes in $V - \{s, d\}$, and computes an outcome consisting of a route selection vector $X = (x_1, \ldots, x_N)$ and a payment vector $p = (p_1, \ldots, p_n)$. In general, we allow multi-path routing. So an element in X, say x_i, $1 \leq i \leq N$, represents the fraction of traffic that will be carried over path i in $\mathbf{R}_{sd}$ during the current session, and p_j, $1 \leq j \leq n$, is the payment to node j for every packet delivered by paths in $\mathbf{R}_{sd}$. Because x_i and p_j are outputs of the mechanism, we write them as functions of the costs, i.e., $x_i \stackrel{\text{def}}{=} x_i(c)$ and $p_j \stackrel{\text{def}}{=} p_j(c)$. To simplify the presentation, in our subsequent formulation we use the following convenient notations: $c_{-j} \stackrel{\text{def}}{=} (c_1, \ldots, c_{j-1}, c_{j+1}, \ldots, c_n)$, $D_{-j} \stackrel{\text{def}}{=} \bigcup_{1 \leq k \leq n, k \neq j} D_k$, $D \stackrel{\text{def}}{=} D_j \bigcup D_{-j}$, $f_{-j}(c_{-j}) \stackrel{\text{def}}{=} \prod_{1 \leq k \leq n, k \neq j} f_k(c_k)$, and $f(c) \stackrel{\text{def}}{=} f_j(c_j) f_{-j}(c_{-j}) \stackrel{\text{def}}{=} \prod_{1 \leq k \leq n} f_k(c_k)$.

The truthful LPP routing mechanism is formulated as follows. The objective is to minimize the expected price that s needs to pay for each packet it sends in a session, i.e.,

$$\text{minimize}_{(X,p)} \quad U_s(X, p) = \int_D \sum_{j \in V} p_j(c) f(c) dc. \tag{1}$$

This objective is also in line with the minimization of the total payment of s over all sessions for a long-lasting flow. Our truthful routing mechanism is subject to the following constraints:

Incentive Compatibility Constraint: For each packet delivered over the route of the underlying session, the expected profit of node j for reporting cost $\tilde{c}_j$ is given by

$$\int_{D_{-j}} \left(p_j(\tilde{c}_j, c_{-j}) - c_j \sum_{i \in \mathbf{R}_{sd}^{(j)}} x_i(\tilde{c}_j, c_{-j}) \right) f_{-j}(c_{-j}) dc_{-j} \tag{2}$$

where $\mathbf{R}_{sd}^{(j)}$ is the subset of paths in $\mathbf{R}_{sd}$ that traverse node j. At the same time, the expected profit of node j for reporting its true cost c_j is given by

$$U_j(X, p, c_j) = \int_{D_{-j}} \left(p_j(c) - c_j \sum_{i \in \mathbf{R}_{sd}^{(j)}} x_i(c) \right) f_{-j}(c_{-j}) dc_{-j} \tag{3}$$

The IC constraint requires that

$$U_j(X, p, c_j) \geq \int_{D_{-j}} \left(p_j(\tilde{c}_j, c_{-j}) - c_j \sum_{i \in \mathbf{R}_{sd}^{(j)}} x_i(\tilde{c}_j, c_{-j}) \right) f_{-j}(c_{-j}) dc_{-j}, \quad \forall \tilde{c}_j \geq 0 \tag{4}$$

Individual Rationality Constraint: This constraint requires that node j participates in the relay only when its expected profit is nonnegative, i.e.,

$$U_j(X, p, c_j) \geq 0. \tag{5}$$

Multi-path Constraint: This constraint says that the sum of the fractions of traffic carried over various paths must equal to the total traffic volume, i.e.,

$$\sum_{i=1}^{N} x_i(c) = 1. \tag{6}$$

Node Capacity Constraint: The aggregate traffic of the sub-flows that traverse the same node should not exceed the node's capacity, i.e.,

$$\sum_{i\in\mathbf{R}_{sd}^{(j)}} x_i(c)R \leq b_j, \forall j \in V \tag{7}$$

where R is the flow rate demand. Note that in our formulation, the node cost is defined for each packet relayed by that node, whereas payment, price, and profit are with respect to each packet delivered over the (multi-path) route. Hereafter, we use the notation i and j to refer to a path and a node, respectively. We follow these norms in all our subsequent sections, unless indicated otherwise.

IV. LPP Without a Node-Capacity Constraint

The main difficulty in solving the LPP problem is that the feasible paths between s and d are not node-disjoint. Therefore, the traffic volumes carried by different nodes are not independent. This inter-dependence, which appears in the IC (4) and the node-capacity constraint (7), prevents us from directly using the Myerson's optimal auction theory [10]. In this section, we first consider a simplified version of the LPP formulation, by ignoring the node-capacity constraint in (7). The resulting mechanism will still be truthful, because the IC and IR constraints are still being accounted for.

Our analysis of the simplified problem proceeds as follows. We first simplify the IC constraint (4). For node j, the fraction of traffic it expects to relay given that its cost is c_j can be calculated as

$$Q_j(c_j) \stackrel{\text{def}}{=} \int_{D_{-j}} \sum_{i\in\mathbf{R}_{sd}^{(j)}} x_i(c_j, c_{-j}) f_{-j}(c_{-j}) dc_{-j} \tag{8}$$

Based on of $Q_j(c_j)$, we have the following lemma.

Lemma 1: The IC constraint in (4) is equivalent to the following two conditions:
(1) Monotonicity: If $c_j^{(1)} \geq c_j^{(2)}$, then $Q_j(c_j^{(1)}) \leq Q_j(c_j^{(2)})$;
(2) $U_j(X, p, c_j) = \int_{c_j}^{w_j} Q_j(\tau_j)d\tau_j + U_j(X, p, w_j)$

Proof: The proof is provided in our technical report [13]. ■

Based on Lemma 1, the simplified LPP problem can be reformulated as follows.

Lemma 2: The following formulation is equivalent to the simplified LPP problem defined in Section III: the optimal route selection vector X is the solution to the following optimization problem

$$\begin{array}{ll} \text{minimize} & \sum_{1\leq j\leq n} \int_D \left[c_j + \frac{F_j(c_j)}{f_j(c_j)}\right] \sum_{i\in\mathbf{R}_{sd}^{(j)}} x_i(c) f(c) dc \\ s.t. & \\ & \sum_{i=1}^{N} x_i(c) = 1 \end{array} \tag{9}$$

where $F_j(c_j) = \int_{v_j}^{c_j} f_j(\tau_j)d\tau_j$ is the c.d.f. of c_j. In addition, the truthful payment to each node is given by $p_j(c) = c_j \sum_{i\in\mathbf{R}_{sd}^{(j)}} x_i(c) + \int_{c_j}^{w_j} \sum_{i\in\mathbf{R}_{sd}^{(j)}} x_i(\tau_j, c_{-j})d\tau_j$, for $1 \leq j \leq n$.

Proof: The proof follows the method used in [10]. The details are provided in [13]. ■

According to Lemma 2, we can resort to the new formulation in (9) to find the solution to the simplified LPP problem. Denote $h(c) \stackrel{\text{def}}{=} \sum_{1\leq j\leq n} \left[c_j + \frac{F_j(c_j)}{f_j(c_j)}\right] \sum_{i\in\mathbf{R}_{sd}^{(j)}} x_i(c)$. An inspection of (9) shows that this formulation actually minimizes the expected value of $h(c)$ given the distribution of $f(c)$. A simple probabilistic argument says that the expected value will be minimized if $h(c)$ is minimized over every c. This gives rise to the following lemma, which reduces our problem from a randomized setup to a deterministic one.

Lemma 3: Given the cost vector c, the LPP route selection problem is given by the following optimization problem:

$$\begin{array}{ll} \text{minimize} & h(c) = \sum_{1\leq j\leq n} \left[c_j + \frac{F_j(c_j)}{f_j(c_j)}\right] \sum_{i\in\mathbf{R}_{sd}^{(j)}} x_i(c) \\ s.t. & \\ & \sum_{i=1}^{N} x_i(c) = 1 \end{array} \tag{10}$$

and the truthful payment is given by

$$p_j(c) = c_j \sum_{i\in\mathbf{R}_{sd}^{(j)}} x_i(c) + \int_{c_j}^{w_j} \sum_{i\in\mathbf{R}_{sd}^{(j)}} x_i(\tau_j, c_{-j})d\tau_j, \quad 1 \leq j \leq n. \tag{11}$$

Regarding the solution of (10), we have the following results.

Theorem 1: In the simplified LPP problem, for each c, the optimal route contains only one path, which is given by $R_{sd}^o(c) = \arg\min_{\forall R_{sd}^{(i)}\in\mathbf{R}_{sd}} (\sum_{j\in R_{sd}^{(i)}} \left[c_j + \frac{F_j(c_j)}{f_j(c_j)}\right])$, where $R_{sd}^{(i)}$ denotes the ith path in $\mathbf{R}_{sd}$, $1 \leq i \leq N$. Thus, the optimal route selection vector is $X^o(c) = (0, \dots, 0, 1, 0, \dots, 0)$, where the non-zero element corresponds to the optimal path R_{sd}^o.

Proof: We rewrite $h(c)$ according to the routes in $\mathbf{R}_{sd}$, i.e.,

$$h(c) = \sum_{1\leq i\leq N} \left(\sum_{j\in R_{sd}^{(i)}} \left[c_j + \frac{F_j(c_j)}{f_j(c_j)}\right] \right) x_i(c). \tag{12}$$

Denote $\xi_j \stackrel{\text{def}}{=} \left[c_j + \frac{F_j(c_j)}{f_j(c_j)}\right]$. Note that for a given c, ξ_j is constant for all $1 \leq j \leq n$. Accordingly, for each path i, the term $W_i \stackrel{\text{def}}{=} \left(\sum_{j\in R_{sd}^{(i)}} \xi_j\right)$ is also a constant. Therefore, for a given c, problem (10) becomes a linear program (LP) of the form:

$$\begin{array}{ll} \text{minimize} & \sum_{i=1}^{N} W_i x_i \\ s.t. & \\ & \sum_{i=1}^{N} x_i = 1. \end{array} \tag{13}$$

It is straightforward to see that the optimal solution to the above LP is $X^o = (0, \dots, 0, 1, 0, \dots, 0)$, where the index of the non-zero element is $i^o = \arg\min_{1\leq i\leq N}(W_i)$. This proves Theorem 1. ■

Theorem 1 suggests the following algorithm for computing the LPP and the related payments. For a given c, we use $\xi_j(c_j)$ as the weight of node j. The LPP is simply the shortest path from s to d w.r.t. ξ_j. Since ξ_j is a function of c_j, it may also be considered as the *virtual cost* of node j. Because now the optimal route contains only one path, the payment can be largely simplified: Equation (11) shows that $p_j(c) = 0$ if node j is not included in the shortest path. Otherwise, $p_j(c) =$

$\min(w_j, \bar{c}_j)$, where $\bar{c}_j$ is the cutoff cost of node j, beyond which node j will not be included in the LPP. This cutoff cost can be computed in the virtual cost domain. Specifically, in the virtual cost domain, let ζ denote the difference in length between the shortest path that traverses node j and the shortest path that does not traverse node j. If the virtual cost of node j grows from $\xi_j(c_j)$ to $\xi_j(c_j)+\zeta$, node j will not be included in the LPP. So $\bar{c}_j = \xi_j^{-1}(\zeta + \xi_j(c_j))$, where ξ_j^{-1} denotes the inverse of the function ξ_j. A pseudo-code description of the above process is given in Algorithm 1.

Algorithm 1 Computing LPP and Payments without a Node-Capacity Constraint

INPUT: $c = (c_1, \ldots, c_n)$
OUTPUT: LPP and $payments$ to nodes
1: **for** $j = 1$ to n **do**
2: $\quad \xi_j \Leftarrow c_j + \frac{F_j(c_j)}{f_j(c_j)}$
3: **end for**
4: $LPP \Leftarrow$ shortest path from s to d w.r.t. weight ξ_j's
5: $minlength \Leftarrow$ length of(LPP)
6: $payments(j) \Leftarrow 0, \quad \forall j \notin LPP$
7: **for all** nodes j in LPP **do**
8: $\quad length\_runnerup(j) \Leftarrow$ length of the shortest path that does not traverse node j
9: $\quad virtual\_cutoff\_cost(j) \Leftarrow length\_runnerup(j) - minlength$
10: $\quad payments(j) \Leftarrow \min(\xi_j^{-1}(virtual\_cutoff\_cost(j)), w_j)$
11: **end for**

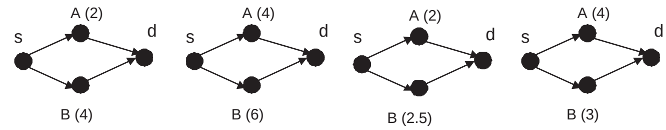
Theorem 2: The route selection and payment mechanism given in Algorithm 1 is truthful and minimizes the expected price of the resulting route.
Proof: The proof is straightforward based on our previous discussion. ∎

In Algorithm 1, the computation of LPP (line 4) involves finding a shortest path. Because all node weights are non-negative, this can be done using Dijkstra's algorithm in $\mathcal{O}(m + n \log n)$ time. It is easy to see that overall, the worst-case running time of Algorithm 1 is $\mathcal{O}(mn + n^2 \log n)$.

A. Examples

To better understand how Algorithm 1 operates, consider the example in Figure 1. Two alternative paths are available from s to d, via node A or B. Suppose the true costs c_A and c_B are uniformly distributed over $[0, 10]$ and $[2, 10]$, respectively. So their virtual costs are given by $\xi_A(c_A) = 2c_A$ and $\xi_B(c_B) = 2c_B - 2$, respectively. We first consider the situation in sub-figure (a), where $c_A = 2$ and $c_B = 4$ for the underlying session. The virtual costs are then computed as $\xi_A = 4$ and $\xi_B = 6$, as shown in sub-figure (b). Algorithm 1 chooses the path $s \to A \to d$ as the LPP, and computes the virtual cutoff cost of node A as 6, which is then mapped to the actual cutoff cost of node A according to the inverse function $\xi_A^{-1}(y) = 0.5y$, giving $\bar{c}_A = 3$. This is smaller than $w_A = 10$, so node A is paid 3 and the price for the LPP $s \to A \to d$ is 3. In contrast, even though the LCP computed according to the VCG algorithm is also $s \to A \to d$, its price is 4, which is 33% higher than the price under LPP.

Note that the LCP may not always be a LPP. Consider the situation in sub-figure (c), where $c_A = 2$ and $c_B = 2.5$. Following the same procedure of the previous example, Algorithm 1 chooses $s \to B \to d$ as the LPP, with a price of 3.25. The VCG algorithm will choose $s \to A \to d$ as the LCP, with a price of 2.5. So here LPP is different from LCP. Note that the higher price paid by the LPP in this example does not contradict with the optimization objective that the LPP's expected (or average) price is minimized. The higher price paid by LPP in some situations is needed to maintain its truthfulness in expectation.



(a) Example 1 (b) Virtual cost domain of example 1 (c) Example 2 (d) Virtual cost domain of example 2

Fig. 1. Examples of LPP without a node-capacity constraint (the cost and virtual cost of a node are indicated between brackets).

V. LPP WITH A NODE-CAPACITY CONSTRAINT

In this section, we study the full-fledged LPP problem with a node-capacity constraint. Such a constraint is needed when the source rate demand is greater than the minimum node capacity in the OSA network.

A. Optimal Route Selection

Based on Lemma 3 and Theorems 1, the inclusion of the node-capacity constraint leads to the following formulation for the optimal route selection:

$$\begin{aligned} \text{minimize}_{(x_1,\ldots,x_N)} \quad & \textstyle\sum_{i=1}^{N} W_i x_i \\ s.t. \quad & \textstyle\sum_{i=1}^{N} x_i = 1 \\ & R \textstyle\sum_{i \in \mathbf{R}_{sd}^{(j)}} x_i \le b_j, \forall j \in V \end{aligned} \tag{14}$$

An inspection of (14) shows that this is a LP. However, the main challenge in solving this problem using a conventional LP solver is that, in practice it is difficult to enumerate all the paths from s to d. So it is difficult to explicitly express the formulation (14). This hinders the operation of the LP solver, because an explicit formulation of the problem is needed for these solvers to construct and navigate through the space of feasible solutions. Here, we follow a different method to solve (14). We first investigate the structure of the optimal solution to (14), given the existence of such a solution. We then design algorithms that directly construct the optimal solution, even though in practice the explicit expression of the problem is hard to express.

Theorem 3: Algorithm 2 is a greedy approach that finds an optimal solution to (14), given the existence of such a solution.
Proof: Note that (14) belongs to the class of min-cost flow problems, but with non-negative nodal weights/capacities. It also has the additional feature that two equal sub-flows in oppositive directions do not cancel each other. Algorithm 2 is actually a modification of the Ford-Fulkerson algorithm [3], in which the search for an augmenting path is done by finding the shortest path w.r.t. the nodal weights ξ_j's. Algorithm 2 is equivalent to sorting the paths in $\mathbf{R}_{sd}$ increasingly according to their length W_i and then allocating traffic to paths sequentially according to their ranking, until all the traffic demand is allocated. Each path is allocated an amount of traffic up to the capacity of its bottleneck node. The basic idea of the proof is to show that any other feasible traffic allocation can always be modified to the above traffic allocation without increasing

Algorithm 2 Computing LPP Under a Node-Capacity Constraint

INPUT: $c = (c_1, \ldots, c_n)$
OUTPUT: LPP

for $j = 1$ to n **do**
  $\xi_j \Leftarrow c_j + \frac{F_j(c_j)}{f_j(c_j)}$
end for
STEP 1: Find the shortest-path from s to d on graph G w.r.t. ξ_j's.
STEP 2: Find the bottleneck node j^* on this path. Allocate a fraction of traffic $b(j^*)/R$ from the flow to this path. Update the capacity of each node on this path by subtracting $b(j^*)$, the portion that has been used by the underlying shortest path, from its original capacity. Delete node j^* from G, along with other possible bottleneck nodes whose capacities become 0.
STEP 3: Repeat STEPs 1 and 2 until all traffic has been allocated or no additional shortest-path in STEP 1 can be found. In the former case, the sequence of paths found by the procedure along with the associated traffic allocation is an optimal solution to (14). If the latter case happens, it means that an optimal solution to (14) does not exist.

the objective function and without violating any constraint in (14). The detailed proof is given in [13], and is omitted here due to space limitation. ■

Algorithm 2 involves repetitive computation of several shortest paths. Because all weights are non-negative, Dijkstra's algorithm can be used to find the shortest path in each iteration in $\mathcal{O}(m + n \log n)$ time. It is straightforward to see that the total running time of Algorithm 2 is $\mathcal{O}(mn + n^2 \log n)$.

B. Payment Calculation

For the LPP with a node-capacity constraint, the general form of the optimal payment defined in (11) still applies. This is because this general equation is solely decided by the IC and IR constraints, and is not related to whether the node-capacity constraint is present in the formulation. The key challenge in calculating this payment is in computing the integral term in the equation. Note that in Algorithm 2, x_i^o is given only as an implicit function of c_j, so it is not suitable to be used directly in the integration. To calculate the payment, we need to take a closer look at the relationship between node j's traffic and its cost c_j.

A re-examination of Algorithm 2 and its proof indicates that the traffic carried by a node j presents a multi-threshold structure in relation to c_j. More specifically, for a node j that is included in the LPP route, the traffic it carries is the sum of the traffic carried by the paths that are part of this route and that also traverse node j. Denote these paths by $\mathbf{R}_{sd}^{(j)o}$. Algorithm 2 dictates that, given the capacity of each node, the optimal traffic allocation across various paths, i.e., $(x_1^o, \ldots, x_N^o)$, is fully decided by the ranking of the paths according to their weights. As a result, when c_j is increased, the traffic allocation to the paths in $\mathbf{R}_{sd}^{(j)o}$ will change only when the increment of c_j is significant enough to change path ranking. It is not difficult to see that this is a mono-decreasing process, i.e., with the increase in c_j, the amount of traffic allocated to the paths in $\mathbf{R}_{sd}^{(j)o}$ always decreases after each change in ranking, because their ranking only drops with a larger c_j. Finally, no traffic will be allocated to the paths in $\mathbf{R}_{sd}^{(j)o}$, since all traffic has been allocated to the paths ranked before them. At this point, c_j corresponds to the cutoff cost of the simplified LPP problem. The major difference here is that, before c_j reaches the cutoff cost, there exist multiple threshold costs, at which a change in the ranking of the paths happens. Such a multi-threshold structure largely simplifies our payment calculation, because the traffic allocation does not change between two consecutive threshold costs. So, to compute the integral in (11), we only need to find the threshold costs and evaluate the traffic allocation at these particular points.

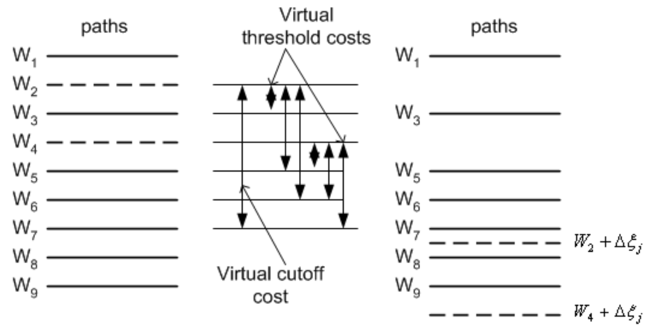


Fig. 2. Calculation of the virtual cutoff cost and threshold costs.

We use an example to illustrate the basic idea of computing the threshold costs and cutoff cost for a node j that is included in the LPP. Consider the example on the left of Figure 2, where paths in $\mathbf{R}_{sd}$ are labeled in the increasing order of their length W_i, defined based on the nodes' virtual cost. Suppose paths 1 to 5 constitute the multi-path LPP constructed according to Algorithm 2. Suppose paths 2 and 4 traverse node j. So, with the increase in ξ_j, the rankings of paths 2 and 4 drop simultaneously. Now consider the situation shown to the right, where path 2 has dropped to a position that no traffic will be allocated to it, but non-zero traffic is still allocated to the path ranked before it, say path 7 in this example. Note that at this time no traffic is allocated to path 4, either. The underlying increment in ξ_j, i.e., $\Delta\xi_j = W_7 - W_2$, is the critical cutoff point for node j. If $\Delta\xi_j < W_7 - W_2$, traffic will still be allocated to path 2, so the traffic carried by node j will be non-zero. But if $\Delta\xi_j > W_7 - W_2$, no traffic passes through node j. So, the virtual cost of node j at this point, i.e., $\xi_j + (W_7 - W_2)$, is the node's cutoff virtual cost. A virtual threshold cost is simply the increment in ξ_j that leads to a change in the rankings of paths 2 or 4. As shown in the middle of Figure 2, in total there are 7 such increments: $W_5 - W_4, W_6 - W_4, W_7 - W_4, W_3 - W_2, W_5 - W_2, W_6 - W_2$, and $W_7 - W_2$ (the last corresponds to the cutoff virtual cost). The actual costs of node j can then be obtained from the corresponding virtual costs by the inverse mapping $\xi_j^{(-1)}$.

In the above calculations, the critical path 7 can be found by excluding node j from the graph G and calling Algorithm 2 to construct another LPP that does not include node j. The longest path in this LPP that has non-zero traffic allocation corresponds to the critical path 7 in this example. Note that there is no need to consider the paths after this critical path, because they will never receive any traffic allocation no matter how big ξ_j becomes. After getting the threshold costs and the cutoff cost, Algorithm 2 can be called to evaluate the traffic allocations at these particular costs. The above procedure for calculating the payments is formalized in Algorithm 3, which is executed after an LPP is found by Algorithm 2.

Algorithm 3 Payment Calculation Under a Node-capacity Constraint

INPUT: LPP
OUTPUT: $payments$ to nodes
1: **for** $j = 1$ to n **do**
2: $\quad \xi_j \Leftarrow c_j + \frac{F_j(c_j)}{f_j(c_j)}$
3: **end for**
4: **for all** $j \notin LPP$ **do**
5: $\quad payments(j) \Leftarrow 0$
6: **end for**
7: **for all** $j \in LPP$ **do**
8: Construct $\mathbf{R}_{sd}^{(j)o}$ from LPP
9: Exclude node j from G and call Algorithm 2 to find the LPP that does not include node j. $l_j^* \Leftarrow$ the length of the longest path in this LPP that has non-zero traffic allocation
10: $\mathbf{R}_{sd}(l_j^*) \Leftarrow$ {paths from s to d whose length is not longer than l_j^*}$-\mathbf{R}_{sd}^{(j)o}$
11: $k \Leftarrow 1$
12: **for** each path $r \in \mathbf{R}_{sd}^{(j)o}$ and each path $u \in \mathbf{R}_{sd}(l_j^*)$ **do**
13: threshold virtual cost $\xi_j^{(k)*} \Leftarrow \max\{$length of path $u -$ length of path $r, 0\} + \xi_j$
14: threshold cost $c_j^{(k)*} \Leftarrow \min(\xi_j^{(-1)}(\xi_j^{(k)*}), w_j)$
15: Call Algorithm 2 to evaluate the optimal traffic allocation $X(c_j^{(k)*}, c_{-j})$
16: $k \Leftarrow k + 1$
17: **end for**
18: $K \Leftarrow$ number of threshold costs, including the cutoff cost
19: Sort $c_j^{(k)*}$'s in an increasing order
20: $payments(j) \Leftarrow c_j \sum_{i\in\mathbf{R}_{sd}^{(j)}} x_i(c_j, c_{-j}) + \sum_{k=1}^{K-1} \sum_{i\in\mathbf{R}_{sd}^{(j)}} x_i(c_j^{(k)*}, c_{-j})(c_j^{(k+1)*} - c_j^{(k)*})$
21: **end for**

The computational complexity of Algorithm 3 is $\mathcal{O}(Kmn^2 + Kn^3 \log n)$, where K is the number of threshold costs for a node j in the LPP. In practice, the value of K has a big impact on the overall computational complexity. For each node j, K is at most the product of the number of paths in $\mathbf{R}_{sd}^{(j)o}$ and in $\mathbf{R}_{sd}(l_j^*)$ (defined in line 10 of Algorithm 3). Intuitively, this implies that if the number of paths included in the LPP is large, then K will be very large. This scenario happens when the source rate demand is much larger than a node capacity, such that the flow has to be split among several sub-flows. When the rate demand of the source is low, our simulations show that Algorithm 3 is fast, because of the small number of threshold costs at each node.

C. Examples

We illustrate the operation of Algorithms 2 and 3 using the topology in Figure 3 (a), where s wants to send a flow of rate 1 to d. The underlying cost and capacity of a node are shown in the figure in the form (c_j, b_j). We assume that the cost of a node is uniformly distributed over $[0, 5]$. So the virtual cost is given by $\xi_j(c_j) = 2c_j$. The virtual costs of various nodes are shown in sub-figure (b). Algorithm 2 first finds path $s \to A \to B \to C \to d$ (length=3) as the shortest path. Because B and C are bottleneck nodes, 0.5 of the original flow is allocated to this path. Accordingly, the residual capacity of A is changed to $1 - 0.5 = 0.5$. Excluding nodes B and C, Algorithm 2 next determines path $s \to A \to E \to F \to d$ (length=4) as the shortest path. Now, A, E, and F are all bottleneck nodes. So 0.5 of the original flow is allocated to this path. Since all traffic of the original flow has been allocated,

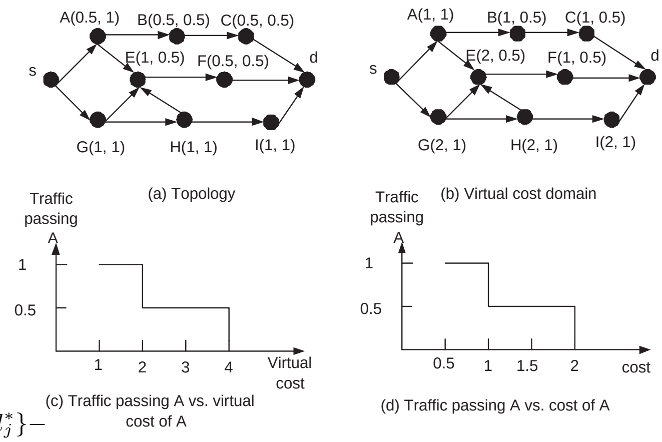


Fig. 3. Example of LPP with a node-capacity constraint.

Algorithm 2 terminates. So the LPP contains two paths with the flow equally distributed between them.

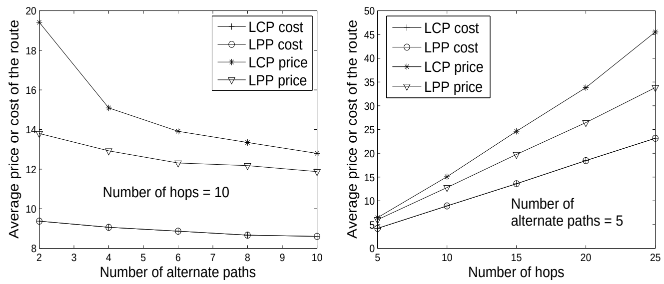
Now consider how Algorithm 3 calculates payments. Consider the payment to A, as an example. Both paths in LPP traverse A, making it the most complicated case of all nodes. To calculate the payment to A, Algorithm 3 first excludes A from the graph and calls Algorithm 2 to find an alternate LPP that does not traverse A. This leads to the alternate LPP: $s \to G \to E \to F \to d$ (weight=5, traffic allocated =0.5) and path $s \to G \to H \to I \to d$ (weight=6, traffic allocated=0.5). The latter is the critical cutoff path. So there are 3 critical increments of ξ_A, namely $5 - 3 = 2$, $6 - 3 = 3$, $5 - 4 = 1$, and $6 - 4 = 2$. For $\Delta\xi_A = 1$, the new virtual cost of A is $1 + 1 = 2$. Beyond this new virtual cost, Algorithm 2 finds the new LPP $s \to A \to B \to C \to d$ that carries 0.5 of the flow, and path $s \to G \to E \to F \to d$ that carries 0.5 of the flow. So overall A carries 0.5 of the flow. We repeat the above process and find that when $\Delta\xi_A = 2$, the LPP consists of the two paths $s \to G \to E \to F \to d$ (traffic=0.5) and path $s \to A \to B \to C \to d$ (traffic=0.5); when $\Delta\xi_A = 3$, the LPP consists of $s \to G \to E \to F \to d$ (traffic=0.5) and path $s \to G \to H \to I \to d$ (traffic=0.5). So the traffic of A is 0.5 and 0, respectively, when ξ_A goes beyond 3 and 4. The traffic of A vs. ξ_A is plotted in sub-figure (c). ξ_A is then inversely converted to the actual cost according to $\xi_A^{-1}(y) = 0.5y$, as shown in sub-figure (d). So the payment to A is $1 \times 0.5 + 1 \times (1 - 0.5) + 0.5 \times (2 - 1) = 1.5$.

VI. Performance Evaluation

In this section, we evaluate the performance of LPP using simulations. The VCG-based LCP algorithm is also simulated for comparison. For an end-to-end flow, the computed cost and price are averaged over sessions to obtain their expected value. We simulate a flow of 500 sessions to ensure the average value is based on a sufficiently large sample size. Our simulations show that in general, similar performance trends are observed under different node cost distributions. So we only show the results under uniformly distributed node costs. The following results are averaged over 10 independent runs.

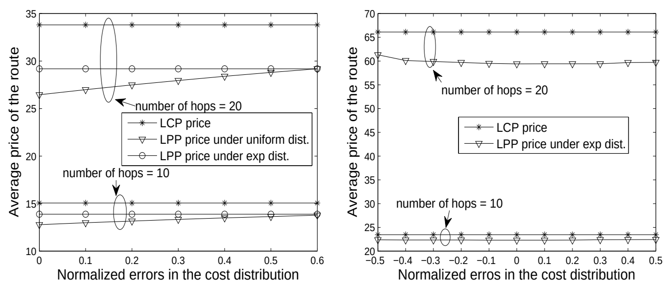
A. LPP Without a Node-Capacity Constraint

In Figure 4, we study the impact of network topology on performance. In these simulations, all paths from the source to the destination are node-disjoint and contain the same number of hops. Node costs are independently and uniformly distributed



(a) Impact of no. of alternate paths (b) Impact of path length

Fig. 4. Impact of topology.



(a) Uniform (b) Exponential

Fig. 5. Sensitivity analysis under various cost distributions.

over $[0, 2]$. Albeit highly idealized, this topology allows us to directly control two important topological parameters: the number of alternate paths and their lengths. Figure 4 shows that a significant saving in price is achieved using LPP over the LCP. At the same time, the cost difference between the two is trivial. This phenomenon indicates that LPP sacrifices little system-wide (social) efficiency in order to ensure a lower payment for the end user. Two additional observations can be made. First, the saving in price is more significant when the number of alternate paths is small (sub-figure(a)). This is because under the VCG algorithm, the price of the LCP is the cost of the second-shortest path. When the total number of alternate paths is small, the monopoly effect of the second-shortest path becomes more significant, leading to a higher price for the LCP. Second, the saving due to LPP is more significant when the path length is larger (sub-figure(b)). This is due to the accumulative saving over various intermediate nodes along the path, which becomes more pronounced with the increase in the number of hops.

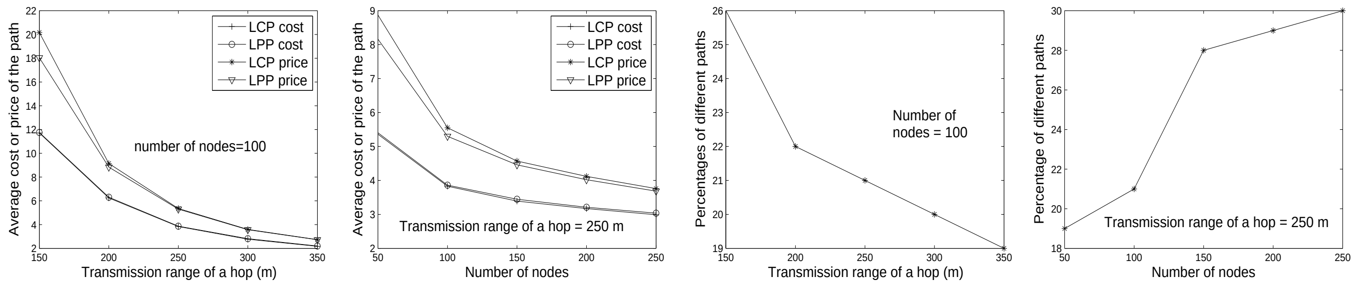
In Figure 5, we study the sensitivity of our algorithm to errors in estimating the distribution of the node cost. We are interested in two types of estimation errors: parameter error and distribution type error. Specifically, we generate the node cost according to a distribution $f^{(1)}$, but we assume the mechanism uses an estimated version, say $f^{(2)}$, to compute the virtual cost. For a parameter error, the distributions $f^{(1)}$ and $f^{(2)}$ are of the same type (function), but differ slightly in the values of their parameters. We show the results for both uniformly and exponentially distributed node costs. For uniformly distributed costs, $f^{(1)}$ has a domain of $[v, w]$ and $f^{(2)}$ has a domain of $[v + 0.5\epsilon(w - v), w - 0.5\epsilon(w - v)]$, where $\epsilon > 0$ is the normalized error (by observing historical samples, the domain of $f^{(2)}$ becomes a subset of that of $f^{(1)}$). For exponentially distributed costs, the rate parameters of $f^{(1)}$ and $f^{(2)}$ are given by $\lambda^{(2)} = (1 + \epsilon)\lambda^{(1)}$, where ϵ represents the normalized error. For an error in the distribution type, $f^{(2)}$ and $f^{(1)}$ are taken as different functions. In particular, when $f^{(1)}$ is uniform, we assume its estimated version, $f^{(2)}$, is an exponential distribution of the same mean. The price of the LPP under both estimation errors is plotted in Figure 5. From this figure, it is clear that as long as the means of $f^{(1)}$ and $f^{(2)}$ are close, both types of errors have only minor impact on the price of the LPP. This phenomenon indicates that our algorithm is insensitive to estimation errors in the node-cost distribution.

In Figure 6, we analyze the performance of LPP under random topologies. We consider a 1000 meter $\times 1000$ meter area. The source and the destination are located at the middle of two opposite sides of the square. Other nodes are uniformly distributed. Heterogeneous spectrum opportunities are simulated. Specifically, we assume that in the middle of this square, there is a 200-meter-radius circular "hot" zone, where the node cost is uniformly distributed between $[0.5, 5]$. For a node outside the hot zone, its cost is between $[0.5, 2]$. Figure 6 shows that the price and cost of LPP and LCP decrease with the node's transmission range and with the number of nodes in the network. The savings in price due to LPP is more significant at small transmission ranges and small numbers of nodes. This can be explained by noting that a smaller transmission range corresponds to a longer path, and a smaller number of nodes means a smaller number of alternate paths from the source to the destination. So these trends are in line with our results in Figure 4. Sub-figures (c) and (d) show the percentage of sessions for which LPP$\neq$LCP. In general, in more than 10% of the sessions, the LPP differs from the LCP. Despite this large difference, sub-figures (a) and (b) show that the cost of the LPP is only slightly higher than the LCP. This phenomenon indicates that the LPP in general tends to employ a node of relatively low cost, but not necessarily the node of the lowest cost.

B. LPP with a Node-Capacity Constraint

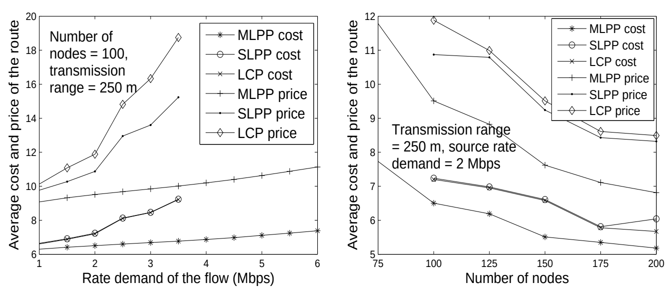
This set of simulations is based on the same random topologies generated for Figure 6, but now each node is associated with a capacity limit (in Mbits/s). For a node in the hot zone, its capacity is randomly selected between 0 and 2 Mbits/s. Otherwise, this capacity is selected between 0 and 5 Mbits/s. Once the node capacity is selected, it does not change throughout the simulation. Due to the lack of counterpart multi-path LCP algorithms, we compare the multi-path route found by LPP, denoted as MLPP in our results, with two single-path routing algorithms. These two algorithms are straightforward extensions of the VCG-LCP and the simplified LPP (the one that does not consider the node capacity constraint), where a node-capacity constraint is imposed. To make these extensions possible, we prune out from the topology those nodes whose capacities are smaller than the rate demand. The LCP and the simplified LPP algorithms are then applied to the residual topology. To distinguish it from the MLPP, the extension of the simplified LPP is denoted as SLPP.

Our simulation results are given in Figure 7. It is clear that the cost and price of MLPP are significantly smaller than its single-path counterparts. In addition, the figure shows that one problem of single-path routing algorithms is that the



(a) Cost/price vs. tx range (b) Cost/price vs. no. of nodes (c) Percentage of LPP≠LCP vs. tx range (d) Percentage of LPP≠LCP vs. no. of nodes

Fig. 6. LPP under random topologies.



(a) Impact of rate demand (b) Impact of number of nodes

Fig. 7. Impact of the source rate demand and number of nodes on path selection.

destination may become unreachable after pruning out nodes of low capacity. As a result, MLPP supports a much higher rate demand by bonding the capacities of multiple paths.

VII. Conclusions

We introduced polynomial-time algorithms for finding the truthful LPP route in an OSA network. Compared with LCP, the adoption of LPP can lower the price paid by end users. The saving in payment using LPP largely depends on the number of alternate paths between the source and the destination and the length (in number of hops) of these paths. In general, the more alternate paths and the longer these paths are, the more saving the LPP can achieve. Although the LPP results in a lower price tag for end users, its cost is only slightly higher than that of the LCP. This indicates that the LPP mechanism only needs to sacrifice a trivial amount of social efficiency in exchange for a lower price tag. Some open topics remain for future work. In this paper, we have focused on the mathematical structures of the LPP mechanism. Protocols that take into account practical issues for its implementation are yet to be developed. In addition, collusion between nodes is not considered in this work. This will be studied in a future work.

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