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High-Throughput Link-Channel Selection and Power Allocation in Wireless Mesh Networks

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ABSTRACT Varying channel conditions, dynamic traffic flows, interference and congestion are the main challenges to achieve high-throughput data delivery in multi-radio multi-channel Wireless Mesh Networks (WMNs). The performance of existing solutions are limited either for using statically computed end-to-end relay paths or myopic forwarding decisions. In this paper, we consider the problem of high-throughput traffic forwarding that involves good quality link selection, channel allocation and power control at each forwarding router. Every router chooses a set of outgoing link-channel pairs and their power allocations through a mixed-integer-non-linear programming (MINLP) solution that maximizes its sum total outgoing flow rate while keeping interference and congestion at minimum. Since, the MINLP optimization function is an NP-hard one, a Reinforcement learning based system for Link-Channel selection and Power allocation, namely RLCP, is developed. A comprehensive design of the RLCP system has been presented containing portrayal of the system state, design of a reputation metric and a mechanism to learn the control policy. We have carried out exhaustive simulations on NS-3 and found the proposed RLCP system to prove its efficacy in terms of aggregated throughput, flow fairness and packet delivery delay.

INDEX TERMS High-throughput, link-channel selection, power allocation, reinforcement learning, wireless mesh networks.

I. INTRODUCTION

The past few years have witnessed tremendous technological development of mesh routers and associated communication protocols, facilitating quick and simple implementation of wireless Internet infrastructure [1], [2]. In addition to desktop machines, a vast diversity of handheld smart devices including mobile phones, tablets, Internet-of-Things (IoT) nodes are astoundingly joining Wireless Mesh Networks (WMNs) for Internet access [3]–[5]. The number of applications running on those devices is exponentially increasing amount of data injected into the network. Moreover, compared to traditional applications, e.g., email and file transfer, the new applications are more delicate to packet loss and delay. Thus, improving network throughput and ensuring timely data delivery in WMNs has emerged as a burning requirement. Even though the mesh routers facilitated with multi-radio multi-channel communications can extend improved data delivery services [6], [7], high fluctuations of channel conditions, traffic flow demands and interference often cause severe congestion and greatly degrade network performance [8], [9]. Accurate capacity quantification of various outgoing link-channel pairs and subsequently choosing some of them along with power allocation might help to achieve high-throughput data delivery in the network. However, such problem is a challenging one caused by the requirement of achieving multiple objectives in a constrained environment.

To secure high-throughput data delivery in WMNs, the state-of-the-art works exploited different approaches - joint routing and channel allocation [10], [11]; routing and

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rate control [12], [13]; and routing, channel allocation and rate control [14], [15]. In [14] and [16], considering the prior knowledge of traffic demand, high capacity and least interfered multiple paths are computed through minimizing co-channel interference. As WMNs are characterized by dynamic channel and load conditions, traffic forwarded over statically computed paths often fail to maintain good throughput. Moreover, centralized solution in [14] hinders its practical applicability in WMNs. A hop-by-hop traffic splitting solution through optimal power allocation over high capacity and least interfered link-channel pairs was developed in [15] to maximize aggregated network throughput. However, use of myopic forwarding decisions following instantaneous network conditions couldn't help to achieve long-term optimal performance under highly dynamic environment.

Moreover, in order to derive a joint optimization solution in reasonable amount of time, the aforementioned approaches relax the primal problem by decomposing it into several subproblems and solving them by greedy or heuristic approaches. Hence, their performances are far from being optimal or they need too long to converge. Recently, it has been observed that the use of machine learning techniques can minimize the gap between the performance and complexity in such challenging network optimization problems [17]. Reinforcement Learning (RL) [18] is one of the most promising tools to devise optimal control policies for joint problems. In RL, one or more agents interact with the environment, initiate actions and exploit the received responses from the environment to grasp the optimal control strategy for a complex problem. While a good number of learning algorithms made their appearance in the context of wireless networking [19], only a few recent works addressed resource allocation problem in WMNs [20], [21].

This paper develops a distributed approach of selecting Link-Channel pairs at each routing hop and allocates Power on those, known as LCP system. It addresses network dynamics by exploiting local and neighboring information and derives forwarding decision considering instantaneous flow demand, interference and congestion. The LCP apportions traffic over good quality link-channel pairs through optimal power allocation aiming to achieve high-throughput data delivery. At the same time, it improves spatial reusability of channels to leverage high-throughput data delivery of neighboring nodes and thus contributes to exalt overall network performance. The main contributions of our work are synopsized as follows:

- We formulate an Optimal LCP problem, namely OLCP, aiming to reduce neighboring interference and link congestion and thus to maximize flow throughput in the class of non-linear mixed-integer programming.
- Since the OLCP solution is NP-hard, we develop a Reinforcement Learning based system for the problem, namely RLCP, that can competently acclimate to complex WMN dynamics.
- By precisely designing the parameters required to represent the system and the reputation metric to drive traffic forwarding actions of the routers, RLCP is able to ensure high-throughput data delivery in the system.
- The validity of RLCP is verified in ns-3 [22]. The results of the simulation study establish the higher proficiency of RLCP over the leading works regarding throughput, latency and fairness.

The organization of the paper is as follows. The related work is documented in Section II. Section III describes the network model and assumptions used in this paper. The joint optimization system and its RL based approach is presented in Section IV. Section V presents the simulation performance results followed by the conclusion in Section VI.

II. RELATED WORKS

In order to ensure high throughput data delivery in WMN, different strategies in the literature have emerged at different operational layers of the network architecture, ranging from channel assignment [19], [23] and congestion control [24], to routing [13], [25].

The path selection in network layer is motivated to improve flow performance considering link/path quality [25], dynamic link conditions [26] and path capacity [27]. In order to mitigate inter-flow interference and avoid bottleneck formation along a routing path, [25] proposed a load-balancing routing metric that computes link quality considering link availability, loss rate and available bandwidth. The conflict graph model is used to compute maximum clique that measures the available bandwidth along an interference free routing path. The routing protocol introduced in [26] computes routing paths considering neighboring contention to improve end-to-end transmission delay.

To allow more concurrent flow transmissions over forwarding links, dynamic channel allocation strategies are employed to maximize network connectivity, minimize link/path interference and enhance path throughput. The channel assignment algorithm in [23], forms a minimum spanning tree, where the link interference weight is proportional to the load weight in the link which in turn is decided by the load present at the node. Among the available channels, the one that exhibits minimum interference weight, is chosen. A learning automata based channel allocation scheme is proposed in [19] that gradually improves network throughput. To improve long-term QoS performance, [28] uses reinforcement learning in spectrum decision that addresses the time varying WMN environment by incorporating channel quality, antenna direction, and the QoS requirements of the applications.

Researchers have also paid high attention in computing traffic forwarding paths and rates over them considering static channel allocation to mitigate channel switching overhead. Authors in [12], propose a multi-path traffic splitting policy targeting to distribute traffic towards multiple gateways in proportion to their queue congestion. A central controller schedules traffic over collision free set of links whose performance is limited by message passing overhead, stale information and longer scheduling delay. In [13], a scalable traffic forwarding solution that uses neighboring information only to select the links and rates to fulfill instantaneous flow demand, thus reacting to real-time dynamics more promptly. However, static channel allocation refrains these systems from exploring better quality channels under high interference and congestion.

To improve flow throughput, channels can be assigned dynamically over the links to mitigate interference and paths can be selected offering higher capacity. Thus, many state-of-the-art works consider jointly solving routing and channel allocation problem. A centralized solution in [10] computes the traffic demand cycles and forwards them over computed sequence of link-channel pairs leading to multiple gateways. In this work, the performance is subject to the accuracy of traffic profiling and limited by fixed forwarding paths. Again, a distributed approach in [11] requires flow scheduling information of the interfering links to find the optimal route. Thus, it amplifies control signaling overhead significantly for the required updates. A hybrid channel allocation strategy in [29] uses fixed radios for end-to-end routing and dynamic radio to communicate over least congested channels under high traffic load.

Since, routing, channel allocation and rate control are interdependent, a good number of research works aim to find control strategies to solve those issues jointly. Solution in [9], computes routes and controls power allocations to activate the desired rates over them. The use of protocol model to find interfering links is unable to efficiently capture the actual interference present in the environment. On the other hand, a data forwarding solution in [8] chooses the least interfered channels and high capacity shortest paths considering the network interference model. In [16], authors assume known traffic demand that experiences deteriorated performance in real dynamic environment. Aiming to improve spatial reusability of channels in neighboring vicinity, authors in [14] compute paths by allocating optimal powers over them. Here, total flow capacity of the paths is maximized whereas interference is kept at minimum. All the aforementioned joint solutions suffer from scalability problem as they require a central controller to compute forwarding decisions. The forwarding decision is taken on stale information that might fail to capture network dynamics. Moreover, they incur huge control signaling overhead thus impacting network throughput. To tackle network dynamics, a distributed optimization framework is developed in [15]. But, due to its slow convergence, authors proposed an alternate greedy solution, sacrificing the optimal performance.

Our proposed joint distributed approach, LCP, for link-channel selection and power allocation is different from the existing literature works in the following ways. Firstly, the LCP utilizes local and single-hop information to instantaneously compute the resource availability and link-channel conditions in the vicinity and distributes the upstream traffic over multiple paths accordingly. Whereas, forwarding traffic over fixed end-to-end paths in [14] and [16] hinders to better capture the network dynamics. Furthermore, in contrast to using greedy allocation policy in [15], the proposed RLCP system exploits historical reputations of link-channel pairs for allocating appropriate powers to achieve better throughput.

TABLE 1. Notations.

Parameter	Description
$\Gamma = (\mathbb{V}, \mathbb{E})$	A graph Γ consisting of nodes V and links E
C	Set of channels
I_v	No. of interfaces of node v
(vw)	Link connecting node v and w
$\mathcal{L}_v^d$	Downstream links of v
$\mathcal{L}_v^u$	Upstream links of u
$p_{(vw)}^c$	Power assigned over link (vw) on channel c
p^{max}	Maximum power
p^{min}	Minimum power
r^{max}	Maximum supported data rate
r^{min}	Minimum supported data rate
$r_{(vw)}^{c,p}$	Link (vw)'s data rate on power p and channel c
$\eta_{(vw)}^c$	Interference present on link (vw) on channel c
$\gamma_{(vw)}^{p,c}$	SINR of link (vw) on power p and channel c

III. NETWORK MODEL

We assume that a wireless mesh network is represented by a graph $\Gamma = (\mathbb{V}, \mathbb{E})$, where $\mathbb{V}$ and $\mathbb{E}$ hold the set of mesh nodes and communication links, respectively. The set of orthogonal channels is represented by $\mathbb{C} = \{c_1, c_2, \ldots, c_k\}$. To allow concurrent transmission over multiple channels, each node v is facilitated with I_V number of interfaces, each of which can operate on a channel chosen from the set $\mathbb{C}_v \subset \mathbb{C}$. We assume a link (vw) between neighboring nodes v and w, if they are communicating to each other over a channel $c \in \mathbb{C}_{(vw)}$, where $\mathbb{C}_{(vw)} = \mathbb{C}_v \bigcap \mathbb{C}_w$. We let a binary variable $x_{(vw)}^c$ hold the value 1, when the link (vw) is activated on channel c; 0 otherwise. We also define a node-channel variable y_v^c, containing 1 if $(vw) \in \mathbb{E}$ and $x_{(vw)}^c = 1$; 0 otherwise. Table 1 indexes all the symbols and acronyms to improve the readability of this paper.

We also assume that, while forwarding traffic over link (vw) on channel c, node v assigns a power level, $p_{(vw)}^c \in \mathbb{P}$, where $\mathbb{P} = \{p^{min}, \ldots, p^{max}\}$, and applies a certain modulation and coding scheme (MCS) to initiate achievable data rate, $r_{(vw)}^{c,p} \in \mathbb{R}$ [16]. Each achievable rate r, ranges between $[r^{min}, \ldots, r^{max}]$ and has a SINR requirement, $\gamma(r)$. The different transmission rates supported by IEEE 802.11a/g system conforming to their minimum SINR values, are listed in Table 2 [16]. A communication link (vw) on channel c and transmission power $p \in \mathbb{P}$ contributes to the SINR experienced at the corresponding receiver w as follows,

$$\gamma_{(vw)}^{c,p} = \frac{p_{(vw)}^c \mathcal{G}_{(vw)}}{\eta_{(vw)}^c + N_0}. \tag{1}$$

In Eq. 1, $\eta_{(vw)}^c$ is the amount of interference sensed at node w due to the coexistence of simultaneous transmissions of neighboring nodes on channel c, N_0 is regarded as Gaussian noise and $\mathcal{G}_{(vw)}$ is the channel gain. At a regular time interval, each router $w \in \mathbb{V}$ exchanges its interference status of each

TABLE 2. IEEE 802.11a/g: SINR vs link capacity.

SINR (dB)	6	7.8	9	10.8	17	18.8	24	24.6
Data Rate (Mbps)	6	9	12	18	24	36	48	54

channel $c \in \mathbb{C}_w$ to its neighboring nodes. Thus, each routing hop $v \in \mathbb{V}$, is cognizant about the interference experienced by each of its downstream links, $(vw) \in \mathcal{L}_v^d$ and it can deduce the achievable rate $r \in \mathbb{R}$, over link (vw), considering the SINR threshold; i.e., $\gamma_{(vw)}^{c,p} \geq \gamma(r)$. Next, we compute the maximum amount of interference tolerable for link (vw) to attain $\gamma(r)$, on power p and channel c is as follows,

$$\eta_{(vw)}^{c,p}(r) = \frac{p_{(vw)}^{c}\mathcal{G}_{(vw)}}{\gamma(r)} - N_0. \tag{2}$$

Next, to measure the quality of a link-channel pair, we define interference degree of a link, $\xi_{(vw)}^{c,p}$, on channel c and power p as follows,

$$\xi_{(vw)}^{c,p} = \frac{\eta_{(vw)}^{c}}{\eta_{(vw)}^{c,p}(r)}, \tag{3}$$

where, $0 \leq \xi_{(vw)}^{c,p} \leq 1$ and higher values indicate higher interference present over link (vw) on channel c.

WMNs mostly act as backbones for forwarding user traffic in the direction to the Internet across multiple gateways, and conversely. In our paper, we represent $\mathcal{L}_v^u$ and $\mathcal{L}_v^d$ to hold the set of upstream and downstream links, respectively, of the forwarding router v. To find $\mathcal{L}_v^d$, each router v uses an appropriate routing algorithm [30], and later the designated links are assigned an appropriate forwarding rate, $r_{(vw)}$, that is restricted to corresponding link's achievable rate, $r_{(vw)}^{c,p}$ and offered rate, $r_{(vw)}^{o}$ [13]. The next section unfolds detail on design components of the proposed data forwarding mechanism.

IV. HIGH-THROUGHPUT LCP

We aim to achieve high-throughput data forwarding in the WMNs through designating an appropriate set of link-channel pairs along with power allocation at each router node. In this section, we first present a system that optimally deduces the forwarding link-channel sets and power allocation (OLCP) over those. As it is proven to be an NP-hard problem, we then design a Reinforcement Learning based distributed link-channel selection and power allocation mechanism, namely RLCP.

A. OPTIMAL LCP

Aiming to maximize aggregated throughput of the network, we formulate an optimization problem for each forwarding router $v \in \mathbb{V}$ in a WMN, that jointly deduces forwarding link-channel pairs and delegates power over those through minimizing neighborhood interference and link congestion. To find a suitable allocation over a link (vw), we first gather all feasible allocation vectors in set $\mathbb{Q}_{(vw)} = \{< x_{(vw)}, c_{(vw)}, p_{(vw)} >\}$, where allocation status $x \in \{0, 1\}$, channel $c \in \mathbb{C}_{(vw)}$ and power $p \in \mathbb{P}$. Next, we compute the set $\mathbb{S}_v = \prod_{(vw)\in\mathcal{L}_v^d} \mathbb{Q}_{(vw)}$ holding all possible allocations for node v. While computing $\mathbb{S}_v$, we remove all the unrealizable and duplicate allocations to moderate the search space. Now, our joint problem opts to find a suitable allocation, $s_v \in \mathbb{S}_v$, so that the aggregated network throughput, τ_{total}, is maximized.

The optimal s_v computation emphasizes on maximizing the capacity-demand ratio, $\sigma(s_v)$, of the router $v \in \mathbb{V}$, which secures the maximum forward of upstream traffic over the selected set of downstreams, defined as follows,

$$\sigma(s_v) = \frac{\sum_{(vw)\in\mathcal{L}_v^d \,\cap\, x_{(vw)}=1} r_{(vw)}}{\sum_{(uv)\in\mathcal{L}_v^u} r_{(uv)}}, \tag{4}$$

where, $\sum_{(uv)\in\mathcal{L}_v^u} r_{(uv)}$ is the total arriving traffic and $\sum_{(vw)\in\mathcal{L}_v^d \,\cap\, x_{(vw)}=1} r_{(vw)}$ is the total outgoing traffic, at router v.

In order to improve data delivery, we opt to disseminate the arriving data flows frontwards through the chosen link-channel sets in proportion to their experienced contention and congestion. Hence, each router v apportions traffic flows over the designated set of link-channel pairs with the stated power levels in s_v, as follows:

$$r_{(vw)} = min\left\{ r_{(vw)}^{o}, r_{(vw)}^{c,p}, \sum_{(uv)\in\mathcal{L}_v^u} r_{(uv)} \times \frac{r_{(vw)}^{c,p}}{\sum_{(vw)\in s_v} r_{(vw)}^{c,p}} \right\}, \tag{5}$$

where, $r_{(vw)}^{o}$ is the rate offered by corresponding downstream node comprehending the experienced congestion, computed as in [13].

While optimizing $\sigma(s_v)$, for each forwarding node $v \in \mathbb{V}$, our secondary goal is to elevate concurrent transmissions of neighboring nodes by improving spatial reusability of channels. Thus, we strive to defeat the total interference degree, $\sum_{(vw)\in s_v} \xi_{(vw)}^{c,p}$, of an allocation s_v, which we materialize by selecting optimal powers over the forwarding links. Accordingly, our joint optimization problem, OLCP, is articulated as follows,

Maximize :

$$\tau_{total} = \underset{s_v \in \mathbb{S}_v}{\textbf{argmax}} \left\{ \sigma(s_v) - \frac{\sum_{(vw)\in s_v} \xi_{(vw)}^{c,p} \times \hat{p}_{(vw)}^{c}}{|s_v|} \right\}, \tag{6}$$

subject to

$$x_{(vw)} \in \{0, 1\}, \quad \forall (vw) \in \mathbb{E} \tag{7}$$

$$y_v^c \in \{0, 1\}, \quad \forall v \in \mathbb{V}, \ \forall c \in \mathbb{C} \tag{8}$$

$$\sum_{c\in\mathbb{C}} x_{(vw)}^{c} \leq 1, \quad \forall (vw) \in \mathbb{E}, \ \forall c \in \mathbb{C} \tag{9}$$

$$\sum_{c\in\mathbb{C}} y_v^c \leq I_v, \quad \forall v \in \mathbb{V}, \ \forall c \in \mathbb{C} \tag{10}$$

$$\sum_{c\in\mathbb{C}} x_{(vw)}^{c} = \sum_{c\in\mathbb{C}} y_v^c, \quad \forall v \in \mathbb{V}, \ \forall c \in \mathbb{C}, \ \forall (vw) \in \mathbb{E} \tag{11}$$

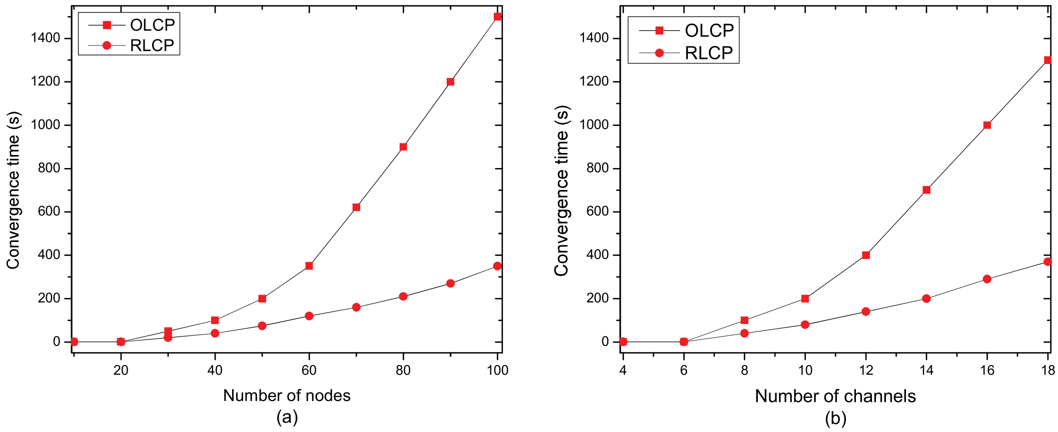


FIGURE 1. Convergence time of LCP systems in WMNs (a) Convergence time vs number of nodes (b) Convergence time vs number of channels.

$$p^{min} \leq p^{c}_{(vw)} \leq p^{max}, \quad \forall (vw) \in \mathbb{E}, \ \forall c \in \mathbb{C} \qquad (12)$$

$$0 \leq r_{(vw)} \leq r^{c,p}_{(vw)} \leq r^{o}_{(vw)} \leq r^{max}, \quad \forall (vw) \in \mathbb{E} \qquad (13)$$

$$\sum_{(uv)\in\mathcal{L}^u_v} r_{(uv)} \geq \sum_{(vw)\in s_v} r_{(vw)}, \quad \forall v \in \mathbb{V}. \qquad (14)$$

The operational state of link (vw) and node v on channel c are depicted in constraints (7) and (8), respectively. The constraint (9) restricts each link (vw) to transmit on more than one channels concurrently. A node is allowed to operate on maximum I_v number of channels simultaneously, stated in constraint (10). The constraint (11) ensures the exclusive binding between each radio-channel pair. The transmission power of a link (vw) on channel c, lies between the threshold values p^{min} and p^{max}, described in constraint (12). The constraint (13) lines the data rate $r_{(vw)}$ on the link (vw) by the smallest value among its achievable rate $r^{c,p}_{(vw)}$, offered rate, $r^{o}_{(vw)}$ and maximum rate, r^{max}. Finally, Eq. (14) states the flow conservation constraint.

The optimization function, developed in Eq. (6), computes link-channel pairs with powers on those that initiate high-throughput data forwarding while inducing less link interference and congestion in the neighborhood. Since the Eqs. (6) - (14) belong to Mixed Integer Non Linear Programming (MINLP) problem class holding combinatorial and continual constraints, we enumerated the convergence time of OLCP along with RLCP (to be discussed in section IV-B) in NEOS Optimization tool [31]. In the experiments, 50 different snapshots of the network scenarios (10 - 100 nodes, 4 interfaces/node, 12 channels, 8 distinct data rates) are provided as input and the resultant convergence times are plotted in Fig. 1(a). The graphs clearly reflect the intractability of OLCP in a typical mesh router. To find the adoption credentials of OLCP and RLCP, we also augmented additional radio resources to the network and observed that with more radio resources OLCP becomes computationally extremely burdensome, as in Fig.1 (b). Thus, we conclude that OLCP's practical implementation in a real-world mesh router is impractical.

B. REINFORCEMENT LEARNING BASED LCP

This section introduces a non-optimal but Reinforcement Learning based LCP system, namely RLCP, which offers high-throughput and sustainable performance and is implementable in mesh networks. Recently, Reinforcement Learning (RL) [18] has been shown to address resource allocation problem by empowering nodes to collect and perceive information from their local operating environment, providing control actions, and exploiting the response obtained from the environment to discover optimal control policies [17]. Considering the time-varying dynamic channel conditions, instantaneous traffic demand and their impacts on performance parameters of WMNs, the proposed RL system, RLCP, only considers the neighboring state information to determine traffic forwarding actions. The system diagram of the proposed RLCP in shown in Fig. 2. We define the state, action and reward of the RLCP system in context of our WMN as follows.

1) STATE

The state is the set of parameters that describes the WMN environment, based on which a router v takes a traffic forwarding decision. These parameters should provide concise information regarding the current network condition. As the traffic forwarding decision depends on the upstream flow demand, offered rates and interference present in each downstream link-channel pair, the state of a RLCP router v can be defined as $\{r_{(uv)}, r^{o}_{(vw)}, \eta^{c}_{(vw)}\}$, $\forall (uv) \in \mathcal{L}^u_v$, $\forall (vw) \in \mathcal{L}^d_v$, $\forall c \in C$.

2) ACTION

A RLCP router v takes an action based on the given system state. For traffic forwarding problem, an action is to determine an allocation vector, s_v, consisting of link-channel selection and power allocation. In order to steer the action towards

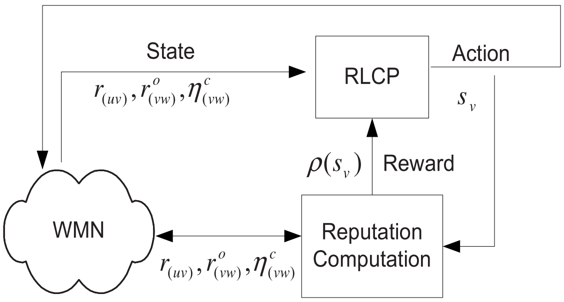


FIGURE 2. System diagram of the proposed RLCP.

high-throughput and sustainable performance, we use a reputation metric, $\overline{\rho}(s_v)$, to quantify the effectiveness of previous action (presented in next the section). A RLCP router maintains a list of allocation vectors, arranged in declining order of their $\overline{\rho}(s_v)$ values. Thus, in order to maximize the data transmission throughput, RLCP system selects an allocation vector having the highest $\overline{\rho}(s_v)$ value.

3) REWARD

Whenever an action is selected, its immediate performance is required to be quantified in order to enumerate its reputation metric. To measure the immediate performance, we need to figure out to what extent it serves our goal. A RLCP router aims to enhance the network throughput by transferring maximum flow over forwarding link-channel pairs, while concerning spatial reusability of channels to allow neighboring nodes to maximize their flow rates. Thus, we require to find (a) how successfully s_v has minimized the backlogged traffic (i.e., maximized the capacity-demand ratio, $\sigma(s_v)$) and, at the same time (2) to what extent it has contributed to minimize neighboring interference. Considering the aforementioned issues, we define instantaneous reputation, $\rho(s_v)$, of the allocation s_v as follows,

$$\rho(s_v) = \sigma(s_v) - \frac{\sum_{(vw)\in s_v} \xi^{c,p}_{(vw)} \times \hat{p}^{c}_{(vw)}}{|s_v|}, \tag{15}$$

where, the value of $\rho(s_v)$ varies between -1 to $+1$. The values greater than 0 represents the reward of the action; on the other hand, values less than 0 is considered as the penalty.

The stability of RLCP system greatly depends on the reputation of the selected allocation which is solely dependent on its long-term performance. While computing the reputation metric $\overline{\rho}_t(s_v)$ at the time instant t, we use exponential weighted moving average (EWMA) formula to prioritize recent observations by using a weight factor α, that exponentially decays for older values computed as follows,

$$\overline{\rho}_t(s_v) = (1-\alpha) \times \overline{\rho}_{(t-1)}(s_v) + \alpha \times \rho_t(s_v). \tag{16}$$

The value of $\alpha = 0.1$ is chosen following numerous experiments in the studied simulation environment.

As an illustrative example, the reputation metric updating experiments of a RLCP router is listed in Table 3 for seven consecutive events e_1 through e_7.

TABLE 3. Reputation of an allocation, s_v.

Event	$\overline{\rho}_{(t-1)}(s_v)$	$\rho_t(s_v)$	$\overline{\rho}_t(s_v)$
e_1	0.4400	0.6000	0.4560
e_2	0.4560	0.7000	0.4804
e_3	0.4804	0.8000	0.5124
e_4	0.5124	0.8000	0.5411
e_5	0.5411	0.7000	0.5570
e_6	0.5570	0.6000	0.5613
e_7	0.5613	0.5000	0.5518
...	...	...	...

4) RLCP OPERATION PROCESS

The operation steps of RLCP is listed in Algorithm 1. At each decision slot, t, the RLCP router considers the current system state as its input, chooses an action, s_v. Initially, the RLCP sorts the allocations in descending order of their reputation metric (line 1). Next, to avoid local optimal decisions and explore better performance resulting from alternative decisions, RLCP picks other actions with very small probability limited by ϵ, known as ϵ-greedy method [32]. On the other hand, the action with the highest reward will be chosen with the probability $1-\epsilon$ (line 4). For the simulation experiments in this paper, we set $\epsilon = 0.1$ after numerous experiments. Next, after executing the selected action, s_v, the router observes the feedback received from the environment and updates the corresponding action's reputation metric, $\rho_t(s_v)$ (lines 9 - 10).

The complexity of Algorithm 1 can be computed in a straightforward way. Initially, quick sort algorithm is used to sort the allocation set W_v in ascending order in line 1, where the worst-case complexity is $O(|W_v| \cdot \log |W_v|)$. The other statements have constant unit time complexities. Therefore, the computational complexity of the algorithm is $O(|W_v| \cdot \log |W_v|)$ in the worst-case.

Algorithm 1 RLCP at any Router $v \in \mathbb{V}$

INPUT: $\sum_{(uv)\in \mathcal{L}^{u}_{v}} r_{(uv)}$; $r^{o}_{(vw)}$, $\forall (vw) \in \mathcal{L}^{d}_{v}$; $\eta^{c}_{(vw)}$, $\forall (vw) \in \mathcal{L}^{d}_{v}$ and $\forall c \in \mathbb{C}_{(vw)}$
OUTPUT: s_v

1. $W_v \longleftarrow \{s^{i}_{v} | s^{i}_{v} \in \mathbb{S}_v \textit{ and } \overline{\rho}(s^{1}_{v}) \geq \overline{\rho}(s^{2}_{v}) \geq \ldots\}$
2. $y \leftarrow$ choose a random value in interval $0 \sim 1$
3. **if** $(y \geq \epsilon)$ **then**
4. $\quad s_v \leftarrow s^{1}_{v}$
5. **else**
6. $\quad s_v \leftarrow$ randomly pick any from $W_v - \{s^{1}_{v}\}$
7. **end if**
8. Execute s_v
9. Compute $\rho_t(s_v)$ using Eq.15
10. Update $\overline{\rho}_t(s_v)$ using Eq. 16

V. PERFORMANCE EVALUATION

In order to rectify the performance facts of our proposed RLCP system and state-of-the-art works JMR [14] and

TABLE 4. Simulation parameters.

Parameter	Value
Network area	$1000m \times 1000m$
Number of mesh routers	50
Wi-Fi Specification	IEEE 802.11a
Path loss model	FrissPathLossModel
RTS and CTS signals	Enabled
Transmission power	$10, 20, \ldots, 100mW$
Noise power density	-174 dBm/Hz
Number of radio interfaces at each router	4-6
Number of available channels in network	12
Packet type	UDP
Packet size	1000 Bytes
Simulation time	1000s

GLCP [15], we implement all three systems in a discrete-event network simulator, ns-3 [22] and discuss the outcomes in this section.

A. SIMULATION ENVIRONMENT

In our experiments, we considered a 50 node WMN, over an area of $1000m \times 1000m$. We deployed the nodes following a uniform random distribution. Each router contains 4 IEEE 802.11a mesh radio interfaces and 12 orthogonal channels are available for communications. Each forwarding link has been assigned a power value from $\mathbb{P} = \{10mW, 20mW, \ldots, 100mW\}$ and the corresponding data rates can be either 6, 9, 12, 18, 24, 36, 48 or 54 Mbps. Routers are assumed to receive UDP packets (1000 bytes each) from Constant Bit Rate (CBR) sources. For each run of the simulation, we activated sources to inject traffic into the network following random uniform distribution.

B. PERFORMANCE METRICS

The effectiveness of the studied traffic forwarding approaches are realized through examining the following 4 metrics - (i) *aggregated flow throughput*: average number of successful bytes reception at destinations per second, (ii) *average end-to-end delay*: the average of latencies experienced by all packets to reach the destinations, (iii) *packet delivery ratio*: the ratio of the total number of packets received by all destinations to the total number of packets transmitted from all sources, and (iv) *flow fairness*: Jain's fairness index is used to measure fairness, that varies between 0 and 1. The index value closer to 1 indicates fair allocation of bandwidth among the flows.

C. SIMULATION RESULTS

We have run each simulation experiment 50 times and plotted the average result in the corresponding graph data point.

1) EFFECT OF INCREASING TRAFFIC LOAD

In this section, we analyze the effectiveness of JMR, GLCP and RLCP systems for various traffic loads in the network. In the experiments, sources from random locations were selected to inject traffic flows, varying from 5 to 30, into the WMN environment, at a rate varying between 5 to 15 Mbps each. Even though the operation process of the proposed scheme does not depend on any specific traffic load generation or distribution policy, we have chosen the random uniform distribution for activating source nodes of the time-overlapping traffic flows, their rates and time durations. In Table 5, we list the time intervals during which short-term, mid-term and long-term traffic flows were activated for $< 10s$, $\geq 10s$ and $< 60s$, and $\geq 60s$, respectively. During the simulation period, on an average, the short, mid and long-term traffic flows constitute approximately 37%, 33% and 30%, respectively.

From Fig. 3(a), we can notice that with higher accumulating traffic loads in the network, resource scarcity intensifies interference and congestion, eventually degrading the aggregated throughput experienced by all the studied approaches. However, the GLCP and RLCP mechanisms offer higher throughputs than that of JMR. Since JMR forwards traffic over statically computed end-to-end paths, it is unable to explore better alternates under high traffic load. Also, JMR incurs significant control signal exchange overhead in higher load conditions. On the other hand, as GLCP allocates higher transmission powers over minimum number of link-channel pairs under high traffic demand and resource scarcity, it intensifies the channel interference and threatens spatial reusability of channels, which eventually lowers aggregated network throughput. However, RLCP system's control policy is learning based, which learns to select the most appropriate link-channel pairs that exhibits higher reputation. Thus, RLCP experiences higher throughput.

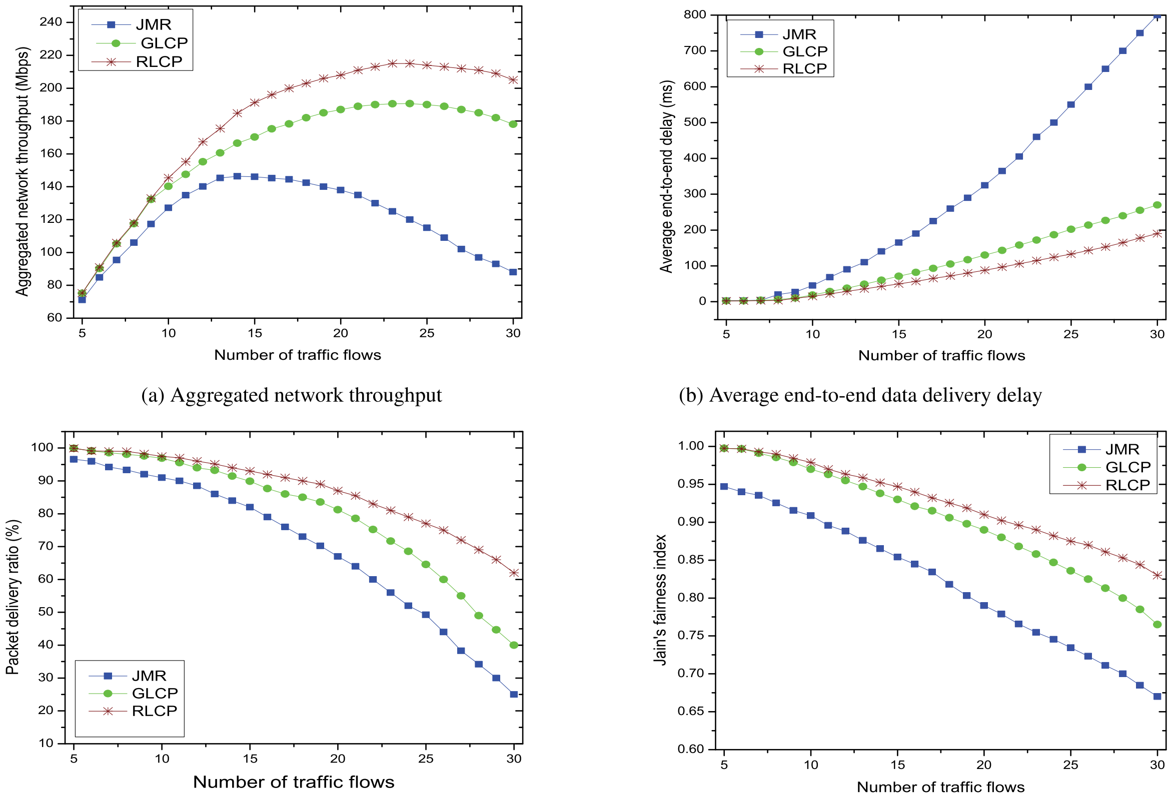
In Fig. 3(b), the average end-to-end packet transmission delay increases with higher traffic load due to increased waiting time at forwarding routers, collisions and retransmissions. Rate control allows the studied approaches to lessen the buffer overflow, but flooding of control messages overwhelms network capacity and packets experience excessive delay at JMR routers. As the forwarding decisions at GLCP and RLCP routers use local and neighboring information, compensation to changing link, channel and load condition is less overhead-prone. Thus, the executions of the appropriate forwarding decisions minimize the packet transmission latency. However, the greedy link-channel selection policy of GLCP experiences unstable performance under higher traffic load. On the other hand, the reward function helps RLCP to learn more stable forwarding paths over the course of time and thus experiencing reduced end-to-end packet transmission delay.

The GLCP and RLCP routers are able to explore alternate downstream link-channel pairs offering higher bandwidth, as opposed to JMR. Thus, higher number of packet delivery increases system reliability, as depicted in Fig. 3(c). However, RLCP's forwarding decision ensures higher reliability as the system is not only conservatively dependent on the learned reputation value of a decision but also puts effort to explore other options through the ϵ - greedy method.

As shown in Fig. 3(d), RLCP system impartially treats all the contending flows by granting them equal share of

TABLE 5. Time intervals of the traffic flows.

Number of traffic flows	Time Intervals							
5 - 30	10s - 100s	80s - 180s	160s - 270s	250s - 370s	350s - 490s	480s - 630s	610s - 770s	750s - 930s



(a) Aggregated network throughput

(b) Average end-to-end data delivery delay

(c) Packet delivery ratio

(d) Flow fairness

FIGURE 3. Performances of the studied data forwarding approaches for increasing number of traffic flows.

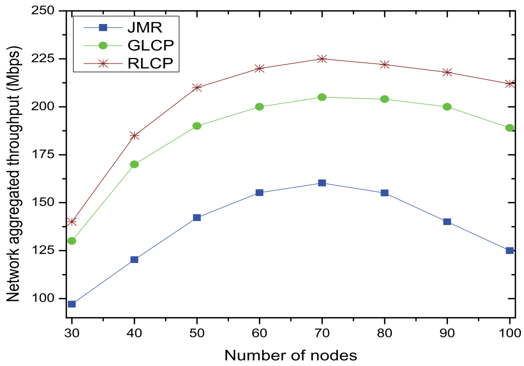
the bandwidth under excessive traffic demand.All the RLCP routers scale their upstream traffic proportionately according to their forwarding capacity. Thus, they cooperate to improve the aggregated, as well as individual's throughput while operating distributively. As JMR forwards traffic over fixed paths, flows in a congested neighborhood experience low throughput than those in a non-congested neighborhood.

2) EFFECTS OF INCREASING NUMBER OF NODES

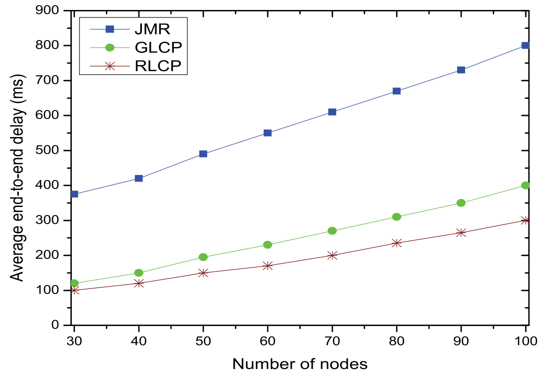
In this section, we investigate the scalability of the studied traffic forwarding mechanisms by considering different dimensions of the WMN. In the simulation experiments, we deployed 30 to 100 nodes over the network maintaining the same node density. In each scenario, we activated around 40% to 50% of the sources to inject traffic flows, following the time intervals listed in Table 5 at a rate between 5 to 15Mbps.

We have plotted the aggregated throughput and average end-to-end packet transmission delay in Fig. 4(a) and 4(b), respectively, as a function of increasing number of nodes in the network. When number of nodes is increased in the network, the GLCP and RLCP systems get more openings to optimally forward traffic that suppresses interference and congestion in the neighborhood and accelerates neighboring flow rates as well. However, in large scale networks, JMR experiences most degraded throughput due to added control traffic between central agent and the routers. The packet delivery delay also climbs up significantly due to increase in path distance between source-destination pairs. Though, GLCP and RLCP experience higher delay in large scale network due to having more congested neighborhood, their delay performances are not impacted by additional control message exchange overhead. Moreover, RLCP system's learning process adopts forwarding decisions targeting to achieve long-term rewards which leads to more stable performance even in a large scale network.

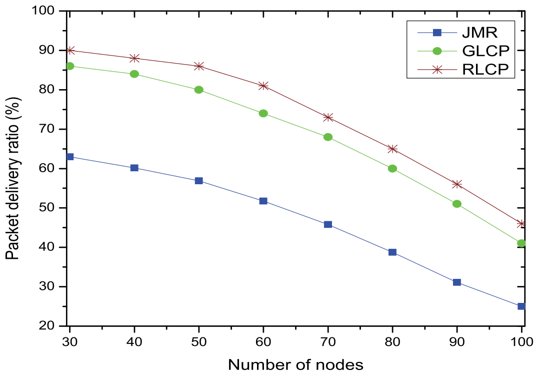
As shown in Fig. 4(c), with increased path distance, timely delivery of control messages to the JMR routers are hindered, which impacts the correctness of JMR decisions and thus downturns packet delivery ratio. In contrast, GLCP and RLCP dynamically deduce the higher capacity link-channel sets and delegate optimal powers on them to forward traffic.



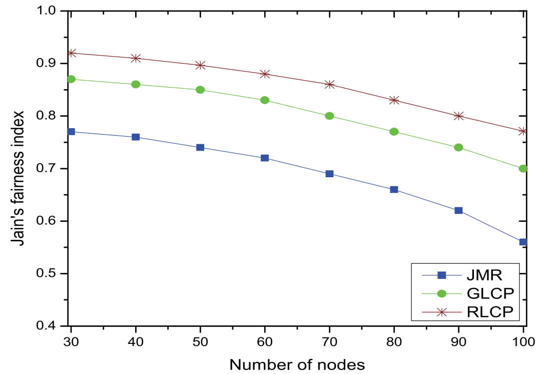
(a) Aggregated network throughput



(b) Average end-to-end data delivery delay



(c) Packet delivery ratio



(d) Flow fairness

FIGURE 4. Performances of the studied data forwarding approaches for increasing number of nodes.

Thus, a router leverages its own as well as the neighborhood capacity, allowing to improve data delivery performance in the network. But, due to the myopic strategy of GLCP, it is unable to compute persisting forwarding decision, lagging behind its packet delivery ratio compared to RLCP.

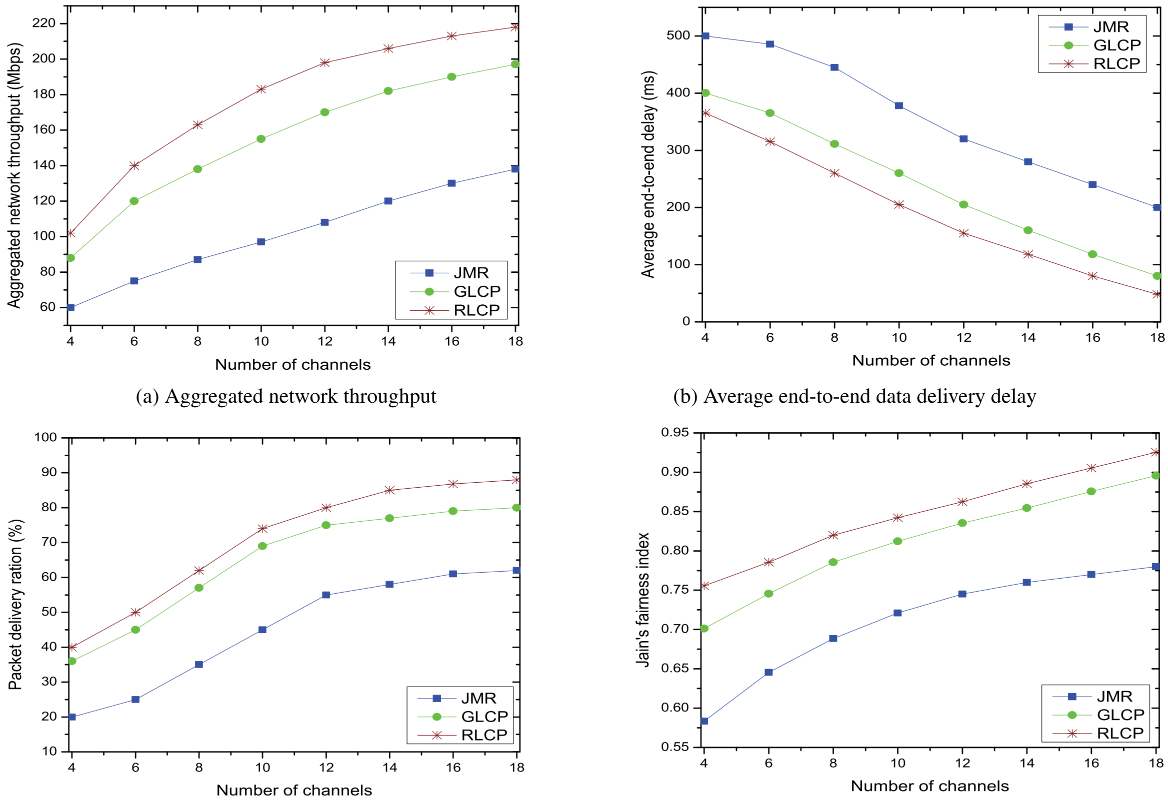
In a multi-hop network, flows originating at furthest from the desired destinations are treated unfairly than those that are closer to the destinations. However, a closer analysis to the simulation trace data and the performance curves in Fig. 4(d) depict that individual traffic flow in our developed RLCP mechanism is granted more rational share of the network resources than the state-of-the-art mechanisms. In large scale networks, centralized forwarding decision is driven by stale information in JMR, as a consequence newly joined flows are deprived from acquiring proportional bandwidth.

3) EFFECTS OF INCREASING NUMBER OF CHANNELS

To analyze the performance of the studied traffic forwarding approaches with augmented radio resources in the network, in our simulation experiments, we varied the number of available channels and recorded the performance metrics. We activated 40% to 50% of the sources to inject traffic flows at a rate between 5 to 15Mbps.

With higher availability of radio resources in the network, routers are able to forward their upstream flows more favourably, upbringing flow performances, as shown in Fig. 5. The data values plotted in Fig. 5(a) reveal that the proposed RLCP system outperforms in terms of attainable throughput even under higher resource scarcity. Our deeper investigation to the simulation trace data reveals that RLCP attains better reward when its forwarding action improves flow throughput as well as minimizes the neighboring interference and congestion. Thus, the reward function improves cooperation among the neighboring nodes, allowing more concurrent transmissions and resulting in improved aggregated network throughput. Whereas, the JMR defers its transmission when radio resources are unavailable and thus degrades system throughput. Again, GLCP greedily picks superior link-channel pairs and puts higher powers in an intention to increase its forwarding rates, which eventually upsurges interference and congestion in the neighborhood, affecting the aggregated network throughput.

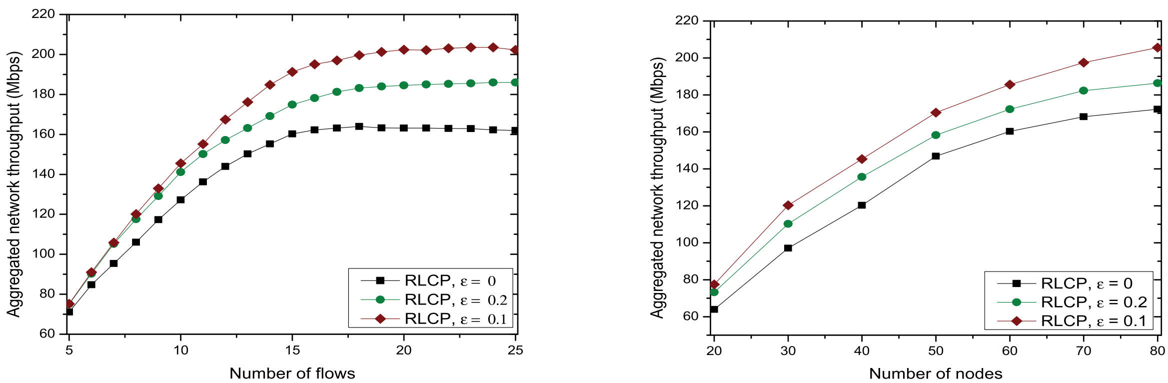
In Fig. 5(b), packet delivery latencies are plotted as a function of increased radio channels in the network. As JMR requires end-to-end control signal relays to compute the fixed paths, it experiences vital delay with few channel resources. Also, traffic forwarding over a statically computed sequence of link-channel pairs restricts JMR from utilizing better quality channels when the pre-computed radio condition degrades. Thus, collisions and retransmissions of data packets affect delivery time markedly. However, the GLCP computes the dimension of an allocation taking into account



(a) Aggregated network throughput (b) Average end-to-end data delivery delay

(c) Packet delivery ratio (d) Flow fairness

FIGURE 5. Performances of the studied data forwarding approaches for increasing number of channels.



(a) Increasing number of flows (b) Increasing number of nodes

FIGURE 6. Impacts of ϵ.

instantaneous channel quality and link capacity that better accommodates the traffic. Finally, the RLCP triumphs over all other mechanisms due to better exploitation of available channels in the vicinity.

Under scarcity of radio resources, traffic delivery significantly drops in the network. But, the GLCP and RLCP systems can mitigate the channel contention and link congestion in the neighboring vicinity, allowing rate adaptation. As sources are guided to scale down their rates, packet loss rate is minimum allowing reliability curves to stay up, as depicted in Fig. 5(c). The reputation metric restricts RLCP to pick unstable channels even under high resource scarcity which in contrary helps it to grant fairer bandwidth share to each traffic flow, as found in Fig. 5(d).

4) IMPACTS OF ϵ

We have also carried out performance evaluations of our proposed RLCP algorithm for various values of ϵ, a small probability with which a router selects an allocation vector randomly (discussed in Section IV-B). We observe in Fig. 6

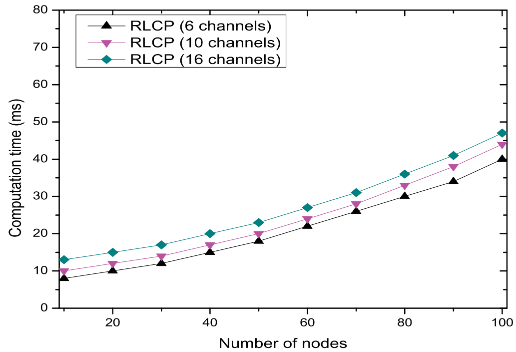


FIGURE 7. Computation time of RLCP.

that the introduction of ϵ in our algorithm gives slightly better performance (in terms of network aggregated throughput) both for varying traffic load and network dimension. We also notice that a smaller value of ϵ (e.g., $\epsilon = 0.1$) is better than larger one (e.g., $\epsilon = 0.2$).

5) COMPUTATION TIME OF RLCP

In Fig. 7, we have plotted the computation time of RCLP algorithm for different network dimensions by varying the number of available channels. From the graphs, it is evident that RLCP's computation overhead is negligible in a typical mesh router.

VI. CONCLUSION

This paper developed an optimal link-channel selection and power allocation mechanism (OLCP) and its reinforcement learning based solution (RLCP) to enhance data delivery throughput of WMNs. The novel design of reputation metric exploiting interference and congestion, and its judicious use in data forwarding decision at each RLCP router are the pivotal contributions of this work. Furthermore, distributed operation process of RLCP following dynamic environmental state feedback, helped it to achieve significant performance improvement. The simulation results demonstrated that as high as 15%, 12% and 10% enhancements in terms of throughput, delay and fairness, respectively, can be achieved by RLCP system. The results also depict the ability of RLCP to better capture highly dynamic link performances at various channels under heavy traffic load condition.

Developing mathematical model to dynamically determine the values of design parameters - α in Eq. 16 and ϵ in Algorithm 1 as well as investigating performances considering simultaneous traffic flows both from and to mesh nodes would be important avenues for future research.

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