Penalty Function Method for Peer Selection over Wireless Mesh Network

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***Abstract*—Appropriate peer selection from the discovered file holders plays a vital role for peer-to-peer (P2P) file sharing over wireless mesh networks (WMNs). When peers choose their own utility-maximizing strategies for coalition and peer formation, the solution is always sub-optimal. Peer formation, based on only application layer information, also results in inefficient use of network bandwidth. When multiple *recipient-peers* try to access the same file from same *source-peer* simultaneously, contention may occur on the shared wireless channel. On the discovery of multiple *source-peers*, corresponding *recipient-peer* may choose optimal *source-peer* in favor of increased network throughput. We formulate the joint peer selection and utility maximization problem as a mixed integer nonlinear programming (MINLP) framework. We also propose penalty-based heuristic genetic algorithm (GA) to solve the MINLP. The results show that our favorable-peer selection strategy results in higher aggregate throughput by selecting optimum *source-peers* with better load distribution and minimum interference.**

I. Introduction

Massive efforts have been made to standardize WMNs which considered as highly promising technology for providing broadband and scalable access to fixed and mobile applications across metropolitan areas. Unlike mobile ad hoc networks (MANETs), where mobility and power consumption pose major challenges; throughput and fairness are the most critical concerns in WMNs. Several cross-layer designs have been proposed in an attempt to maximize the achievable aggregate throughput. The work in [1], proposed a cross-layer design for joint routing and resource allocation of the physical (PHY) and the medium access control (MAC) layers in WMNs. The paper in [2], addressed the joint end-to-end rate optimization and radio resource management problem in wireless orthogonal frequency division multiplexing (OFDMA)-based mesh networks. The optimal network operation is defined in terms of a utility maximization problem subject to link capacity constraints, power and rate control and time-frequency assignment. In [3], the authors implemented optimization method to calculate network throughput with joint rate control, routing and scheduling in a WMN. The authors also addressed the fairness issue and showed that a tradeoff exists between network throughput and the degree of fairness. However, the scheme requires to identify all possible transmission modes in the first step.

P2P over WMNs has received significant attention [4], [5], [6]; a combination of both offers new possibilities, but poses several challenges as well. P2P searching protocol, which relies on overlay network, yields some penalties in terms of bandwidth usage due to a partial removal of routing intelligence of the network layers. The authors in [4] proposed an efficient algorithm for wireless P2P file sharing systems. The algorithm assumes to have full awareness of the underground network topologies and part of the lookup messages are constrained in a local mesh network. However, this paper did not mention about resource allocation procedure. [5] also proposed a network-aware P2P file architecture. This scheme assigns the peers to a network-aware cluster using a network prefix division and thereby enables the files to be searched first with nearby peers. In [6], the authors addressed the issue of increased contention on the shared wireless channel when multiple nodes try to access the same file simultaneously and proposed efficient peer selection scheme. However, this protocol selects potential download peers based on the current load and interference on the download paths for a single receiver at a time.

We want to evaluate the maximum throughput of a P2P file sharing system and thereby identify the factors and their influences on aggregate throughput. We denote a node that wants to retrieve a file as *recipient-peer*. We assume that each *recipient-peer* initiates a peer discovery mechanism to find potential *source-peers*. Any *recipient-peer* may find multiple *source-peers* which yield multiple paths routed from these sources to *recipient-peers*. Other *recipient-peers* may seek same file segments and eventually discover same *source-peer(s)*. However, when multiple *recipient-peers* try to access same *source-peer* simultaneously, contention may occur on the shared wireless channel. Similarly, contention may also occur when multiple *recipient-peers* try to access different content from one *source-peer* simultaneously. Forming peers based on greedy algorithm will always give suboptimal solution. It is possible to improve the overall P2P network in terms of bandwidth utilization and delay minimization through selecting favorable peer employing optimization technique with Network/Application layer information.

We do not make an attempt to propose any new protocol for a P2P file system over WMNs as [4], [5], [6]; rather emphasize on calculating upper bound of the network resource to identify the factors that influence the aggregate throughput. Opposed to previous approaches [1], [2], [3], where optimization is

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implemented to maximize utility for multiple sources and multiple fixed destinations; we consider selecting optimum destinations in favors of maximizing the utility. To the best of our knowledge, we are the first to consider selecting optimum destinations to calculate the upper bound of the aggregate throughput using network-wide optimization. This allows us to gain insight in the influence of routing schemes, and peer selection strategies on the network performance.

II. System Model

We consider a WMN with nodes located at fixed position. Each node consists of a transmitter, a receiver and an infinite buffer and can only receive data in the signal range of communicating nodes if its signal to interference and noise ratio (SINR) is higher than a specified level. We represent the topology of the network by a directed graph $\mathcal{G} = (\mathcal{N}, \mathcal{L})$, where $\mathcal{N} = 1, 2, \ldots, N$ and $\mathcal{L} = 1, 2, \ldots, L$ label all the nodes and links, respectively. Each link $l \in \mathcal{L}$ is represented by an ordered pair (u, v) of distinct nodes, where the presence of link (u, v) means that the network is able to send data from node u to node v.

We understand that a good increase in throughput can be achieved by employing adaptive transmission rates and variable transmit powers. However, our prime goal is to determine the factors that influence aggregate throughput. To keep our problem formulation simple and not to divert from our main investigation, we only consider fixed transmission rates and transmit powers WMN. Transmitter of node u either transmits power P_u or remains silent. G_{uv} denotes the effective power gain between the transmitter of node u and the receiver of node v and is measured by the deterministic fading model, $G_{uv} = K_{uv} d_{uv}^{-\xi}$. Here, d_{uv} is the distance between transmitter u and receiver v, ξ is a constant path loss exponent and K_{uv} is a normalization constant. The normalization constant depends on the radio propagation properties of the environment, and also accounts for the effects of coding gain, spreading gain, beamforming, etc. Also, note that $G_{uu} = 0$. We define thermal noise power at receiver of node u as σ_u. Then the SINR at receiver of node v is

$$\gamma_{uv} = \frac{G_{uv} P_u}{\sigma_v + \sum_{k \in \mathcal{N}, k \neq u} G_{kv} P_k} \tag{1}$$

The capacity of link l of the ordered pair (u, v) is determined by the Shannon capacity model

$$c_l = W \log_2(1 + \gamma_{uv}) \tag{2}$$

where W is the system bandwidth. In our model, we assume that a transmitter of node u only transmits to the receiver of node v if γ_{uv} exceeds target SINR value of γ_l^{tgt}. And the transmission rate with this γ_l^{tgt} is obtained as

$$c_l^{tgt} = W \log_2(1 + \gamma_l^{tgt}) \tag{3}$$

We assume a scheduling-based MAC layer where each scheduling period takes '1' unit time. A scheduling period is further divided into multiple transmission modes. On each transmission mode, multiple non-interfering links may transmit at the same time for a fraction of the unit scheduling period. We use $\mathcal{T} = 1, 2, \ldots, T$ to represent the set of transmission mode. T is sufficiently large $(T > L)$ such that all links get opportunity to transmit for at least once. Let the scalars τ_t represent the fraction of time that transmission mode t is activated and $\sum_{t=1}^{T} \tau_t = 1$. On each transmission mode, a transmitter of node u can only transmit to the receiver of node v if $\gamma_{uv} \geq \gamma_l^{tgt}$. We do not need to generate $\mathcal{T}$ as it is obtained from the results of our network-wide optimization model.

III. Problem Formulation

We formulate the problem of utility maximization through favorable peer selection as a MINLP problem. We label the *recipient-peers* by integers $p = 1, 2, \ldots, P$. For any peer p, number of possible *source-peers* is Q^p and is defined by the set $\mathcal{Q}^p = \{1, 2, \ldots, Q^p\}$. Hence, the total number of *source-peers*, $Q = \sum_p Q^p$. Let s_p^q denotes the end-to-end rate for communication between *recipient-peer* p and *source-peer* q with $q \in \mathcal{Q}^p$. For each peer p, $\hat{s}_p$ denotes the optimum peer among *source-peers* $q \in \mathcal{Q}^p$. To capture the effect of routing scheme on throughput, we consider both fixed and flexible routing.

A. Throughput bound with fixed routing

In case of fixed routing scheme, we assume that each *recipient-peer* initiates a peer discovery mechanism and eventually may discover multiple potential *source-peers.* For each peer p, we define a link layer route matrix $\mathcal{R}^p \in \mathbb{R}_{L \times Q_p}$. The entries r_{lq}^p of $\mathcal{R}^p$ satisfy $r_{lq}^p = 1$, if *recipient-peer* p has an end-to-end (E2E) path at q-th source through link l; otherwise 0. Let y_t^l represents a binary variable which satisfies $y_t^l = 1$ if link l is active on transmission mode t; 0 otherwise. Also, $u(s_p^q)$ denotes the utility function associated with *recipient-peer* p and *source-peers* $q \in \mathcal{Q}^p$ communicating at rate s_p^q. We formulate the MINLP problem as follows.

$$\text{MINLP}: \quad Maximize \quad \sum_p \sum_q^{\mathcal{Q}^p} u(s_p^q) \tag{4}$$

subject to:

$$s_p^q \geq 0, \quad \forall p, q \in \mathcal{Q}^p \tag{5}$$

$$s_p^q \leq \mathcal{M} w_p^q, \quad \forall p, q \in \mathcal{Q}^p \tag{6}$$

$$\sum_q^{\mathcal{Q}^p} w_p^q = 1, \quad \forall p \tag{7}$$

$$\sum_{t=1}^{T} \tau_t = 1, \quad \tau_t \geq 0, \quad \forall t \in \mathcal{T} \tag{8}$$

$$\sum_p \sum_{q \in \mathcal{Q}^p} r_{lq}^p s_p^q \leq \sum_{t=1}^{T} \tau_t c_l^{tgt} y_t^l, \quad \forall l \in \mathcal{L} \tag{9}$$

$$G_{uv} P_u y_t^l + \mathcal{M}(1 - y_t^l) \geq$$

$$\gamma_l^{tgt}\left(\sigma_v + \sum_{k\in\mathcal{N},k\neq u} G_{kv}P_k y_t^l\right), \quad \forall t\in\mathcal{T}, l\in\mathcal{L} \tag{10}$$

$$\sum_{l\in\mathcal{L}^u} y_t^l \quad\leq\quad 1, \quad \forall t\in\mathcal{T}, u\in\mathcal{N} \tag{11}$$

Here, $\mathcal{M}$ is a constant of large value. w_p^q is a binary variable in constraints (6) and (7), which forces all s_p^q to be '0' except '1' for each p, and $q\in\mathcal{Q}^p$. Hence, only one *source-peer* is selected for each *recipient-peer*. The scalars τ_t represent the fraction of unit time that transmission mode t is activated. For our scheduling-based MAC layer, the average transmission rate of link l is $\sum_{t=1}^{T}\tau_t c_l^{tgt} y_t^l$ when constraint in (8) implies. The constraints in (9) guarantees the total traffic across the link l should be less than the average transmission rate of that link. Constraint in (10) imposes that link l is not active if the SINR of the receiver is less than γ_l^{tgt}. Defining $\mathcal{L}^u\subseteq\mathcal{L}$ links at node u, constraint in (11) imposes that transmitter/receiver at each node u transmits/receives data from only one transmitter at time fraction t. The number of variables grows on the order of $\mathcal{O}\left(2\times L\times T + 2\times Q + T\right)$ and the number of constraints grows on the order of $\mathcal{O}\left(5\times L\times T + Q + 2\times P + L + 1\right)$.

B. Throughput bound with flexible routing

We use the term "flex routing" for load balance routing in favor of increased E2E rates. A flow from source peer to a recipient peer may take multiple paths at the same time. To incorporate flexible routing in favor of higher throughput we extend MINLP formulation with the constraint in (12) and also replace the constraint in (9) with the constraint in (13).

$$\sum_{l\in\mathcal{L}_{\mathcal{O}}^u} {}_l x_p^q - \sum_{l\in\mathcal{L}_{\mathcal{I}}^u} {}_l x_p^q = \begin{cases} s_p^q & \text{if } u \text{ is a } \textit{source-peer}, \\ -s_p^q & \text{if } u \text{ is a } \textit{recipient-peer}, \\ 0 & \text{otherwise}, \end{cases}$$
$$\forall u\in\mathcal{N}, l\in\mathcal{L} \tag{12}$$

$$\sum_{p}\sum_{q}^{\mathcal{Q}^p} {}_l x_p^q \leq \sum_{t=1}^{T}\tau_t c_l^{tgt} y_t^l, \quad \forall l\in\mathcal{L} \tag{13}$$

Here, ${}_l x_p^q$ denotes the amount of traffic on link l from the *source-peer* $q\in Q^p$ to the *recipient-peer* p. Constraints in (12) ensures the flow conservation law. For any node other than source and destination, the amount of ingoing flow is equal to the amount of outgoing flow. Also, the net flow leaving at the source and entering at destination is equal to the source rate. Constraint in (13) guarantees that the total amount of traffic on link l, $\sum_p\sum_q^{\mathcal{Q}^p} {}_l x_p^q$ does not exceed the link capacity c_l. The number of variables increases on the order of $\mathcal{O}\left(L\times Q\right)$ and the number of constraints increases on the order of $\mathcal{O}\left(N\times L\right)$.

IV. SOLUTION TECHNIQUE

The optimal solution to the MINLP problem is in general hard to achieve, both in theory and in practice due to the intractability caused by mixed-integer and nonlinear characteristics of decision variables. To achieve the near-optimal results of the MINLP problem, we propose a GA-based heuristic algorithm which is a class of stochastic optimization search methods that mimic the process of Darwinian natural selection. The GA always maintains a large candidate solutions rather than generates a single potential solution.

Since GA is suitable for unconstrained optimizing algorithm; constraint handling is a critical concern when GA applies to nonlinear constrained optimization problems. Penalty and barrier method are among the most common techniques that transform the problem from a constrained optimization to an unconstrained problem for the GA implementation. While the former belongs to exterior-point method, the later belongs to interior-point method. Penalty method adds a penalty function to the objective function for any violation of the constraints and forces the solution to the feasible region and subsequent optimum. Barrier method also adds a penalty-like term to the objective function that acts as a barrier. This ensures that the search always remains to interior-point of the feasible region. Interior-point barrier method requires a feasible starting point. Also it is computationally inefficient to check that search never leaves the feasible domain. Therefore, we prefer exterior-point penalty method. Unlike [7], our approach doesn't require to eliminate integer variables. The solving procedure of MINLP employing penalty-based GA (PGA) is outlined in Algorithm 1 and illustrated as follows:

Algorithm 1: Penalty based GA for solving MINLP

Input : **Network parameters:** $\mathcal{G}$, G_{uv}, P_u, γ_l^{tgt}, c_l^{tgt}, σ_u, T, P, $\mathcal{Q}^p$, $\mathcal{R}^p$
GA parameters: pop_size, p_C, p_M, N_G, $R_{l,i}$
Output : s_p^q, w_p^q, y_t^l, τ_t, ${}_l x_p^q$

begin
  Set up and initialize network and GA parameters;
  Generate initial population $\mathcal{P}^0$;
  for $i\leftarrow 1$ **to** N_G **do**
    for $j\leftarrow 1$ **to** pop_size **do**
      if $\mathrm{mod}\,(j,2)==0$ **then** *Crossover* with p_C;
      Mutate with p_M;
    end
    foreach $p\in P$ **do**
      for $q\leftarrow 1$ **to** Q^p **do**
        if $q=\widehat{w}^p$ **then** $w_p^q=1$;
        else $w_p^q=0$;
      end
    end
    foreach *individual of the current generation* **do**
      if *flex route-scheme* **then**
        Evaluate fitness with penalty for constraints (8, 10, 11, 12, 13);
      else
        Evaluate fitness with penalty for constraints (8, 9, 10, 11);
      end
    end
    Perform *selection* using roulette wheel sampling scheme;
  end
  return s_p^q, w_p^q, y_t^l, τ_t, ${}_l x_p^q$
end

Representation and initialization: The algorithm starts with an initial population $\mathcal{P}^0$ of size pop_size. Each individual in the population is a string entity of artificial chromosome, representing a solution to the problem at hand. The candidate solutions for τ_t, s_p^q, and ${}_l x_p^q$ are derived from the chromosomes of length T, Q, and $L\times Q$. Each of these chromosomes is a binary string and directly coded as a real value within its corresponding bound. The candidate solution for y_t^l is derived from the corresponding element of a chromosome comprising 2-dimensional binary string of length $L \times T$. For optimum peer selection, we define $\widehat{w}^p$, with $p = 1, \ldots, P$ whose candidate solutions are derived from P chromosomes. Each of these chromosome is coded as an integer value and $\widehat{w}^p = q$ is equivalent to $w_p^q = 1$. To generate $\mathcal{P}^0$, we assign random numbers to the binary string. The chromosomes then evolve through successive iterations called generations.

Crossover and Mutation: During each generation, new chromosomes (offspring) are produced using two genetic operations, crossover and mutation. Crossover operator generates offspring by recombining two chromosomes from current generation and thereby provides diversity to the population. The crossover point is chosen with crossover probability p_C. We perform the mutation operation with probability p_M that prevents premature loss of hereditary information by randomly modifying alleles within a chromosome.

Selection: The performance of the penalty method depends on the magnitude of penalty factor. If the penalty factors are too large, the GA based method converges to prematurely solution inside the feasible region. On the other hand, if the penalty factors are too small, this method may divert towards the infeasible region due to the occurrence of excessive violation. Therefore, it is important to choose appropriate penalty factors to maintain the diversity and check the violations at the same time. We propose a GA based penalty function method for solving nonlinear constrained optimization problems. This approach utilizes user defined multi-stage penalty factors for each constraint in the objective function to account for violation. Multi-stage penalty factors depends on the magnitude of the violation of the constraints. Since, $\widehat{w}^p = q$ is equivalent to $w_p^q = 1$; the fitness function is evaluated as the following:

$$Eval(\cdot) = \sum_p \sum_q^{Q^p} \left(u(s_p^q) \times w_p^q\right) - \sum_i \left(R_{l,i} \times \max[0, g_i(\cdot)]\right) \quad (14)$$

Where, $R_{l,i}$ is the penalty factor of the l-th violation level corresponding to i-th constraint. Constraints are rearranged of the form $g_i(\cdot) \leq 0$. Also note that equality constraints $h_j(\cdot)$ are transformed to inequality constraints by $h_j(\cdot) - \epsilon \leq 0$; ϵ is a very small value. We also note that for fix routing method, we are only required to penalize any violation in constraints (8), (9), (10), and (11). Whereas, for flexible routing method, we only penalize any violation in constraints (8), (10), (11), (12), and (13). Constraints are also normalized to avoid any sort of bias toward any of them. We use roulette-wheel selection, that selects the individuals with a probability proportional to their fitness values and thus keep the population size constant. After N_G iterations (generations), the algorithms converge to the best (fittest) chromosomes that represent a near-optimal or suboptimal solution to the problem.

V. Numerical Analysis

We develop a program using C++ to implement the PGA and make use of free *GAlib* (version 2.4.7) tool for our GA based solution [8]. We implement our optimization model on 10 different WMNs with n nodes randomly located in a $1000 \times 1000 m^2$ region. We do not consider Internet gateways in our scenario and concentrate on examining the content delivery within the WMN. We evaluate the ISM frequency band $2.4000 - 2.4835\ GHz$ as described in [2]. The path loss exponent $\alpha = 3$, the normalization constant K_{uv}, the power of each transmitter $P = 100mW$, and the thermal noise at each receiver $\sigma = 3.34 \times 10^{-12}$. We use these parameters to generate the links. With $\gamma_l^{tgt} = 10$ for all $l \in \mathcal{L}$ and $W = 83.5\ MHz$, a link exists if $d_{uv} \leq 85.4m$ with 288.9 $Mbps$ capacity. We use the following α-fair utility functions to implement the familiar objectives: rates maximization (for $\alpha = 0$), proportional fairness (for $\alpha = 1$), and max-min fairness (for $\alpha \to \infty$).

$$U_\alpha(\cdot) = \begin{cases} \frac{(\cdot)^{1-\alpha}}{1-\alpha} & \alpha \geq 0, \alpha \neq 1; \\ \log(\cdot) & \alpha = 1 \end{cases} \quad (15)$$

Although we perform our simulation on several networks, we present results for only mid-size network consisting 8 nodes and 17 links due to space limitation and similar pattern in the results.

1) The influence of peer selection strategy: We name the optimal peer obtained from MINLP formulation as *favorable-peer*. Here, we compare our favorable peer selection approach with two other existing peer selection strategies: random peer and closest peer. At first we show the results that shows the efficacy of *favorable-peer* selection strategy over two other strategies *random-peer* and *closest-peer* in terms of aggregate throughput. The *closest-peer* selection strategy is necessary based on the shortest-path route algorithm. We implement the *favorable-peer* strategies for both fixed routing (shortest-path), and flexible routing and mark them as FP-FIX and FP-FLEX, respectively. We also tag *random-peer* and *closest-peer* selection scheme as RP-FLEX and CP-FIX, respectively. We consider aggregate throughput of the network as our key metric. We define the degree of replication, d^{rep} as the ratio of *source peers* over *recipient-peers*. For an example, consider $P = 4$. If the number of *source-peers(s)* for *recipient-peer 1, 2, 3* and *4* are 2, 1, 3 and 1; then $d^{rep} = (2 + 1 + 3 + 1)/(4) = 1.75$. We compare the peer selection schemes in terms of aggregate throughput for various measure of fairness. Due to space constraint, we only present the results for proportional fairness ($\alpha = 1$). Fig. 1 depicts the normalized aggregate throughput in terms of degree of replication. With PGA, both FP-FLEX and FP-FIX peer selection methods show increased normalized aggregate throughput with the increase in degree of replication. FP-FLEX and FP-FIX peer selection methods also perform better in terms aggregate throughput than that of CP-FIX and RP-FLEX peer selection methods. For example, with $d^{rep} = 1.0$, there is no significant difference in aggregate throughput for all peer selection strategies with the absence of multiple *source-peers* for any *recipient-peer*. And with $d^{rep} = 1.8$, the aggregate throughput in FP-FIX peer selection strategy is 15% and 20% higher than that of CP-FIX and RP-FLEX selection strategy, respectively. Moreover, with $d^{rep} = 1.8$, FP-FLEX

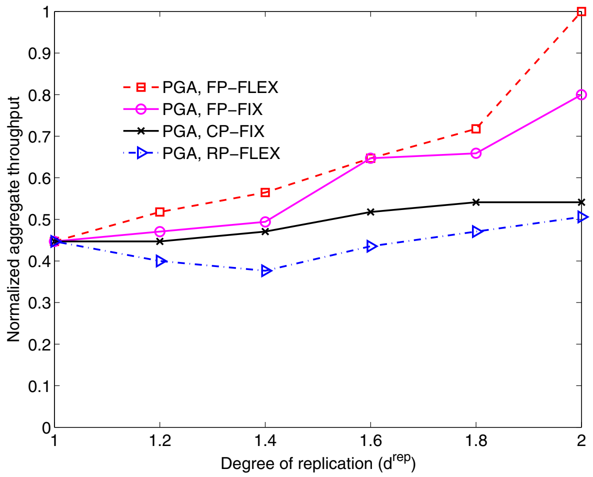

Fig. 1. Normalized aggregate throughput in terms of degree of replication for proportional fairness ($\alpha = 1$).

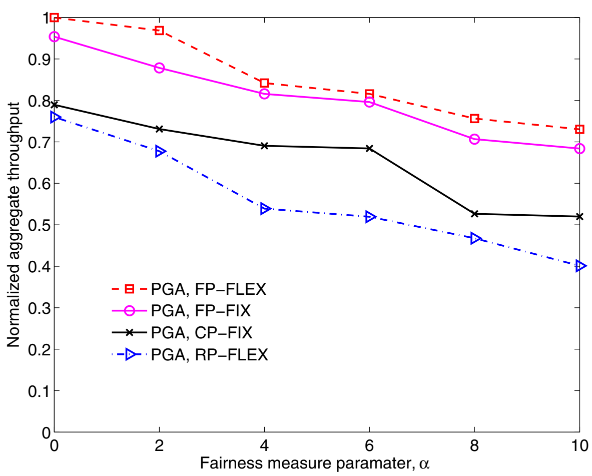

Fig. 2. Tradeoff characteristics between normalized aggregate throughput and fairness.

selection strategy exhibits 4% higher throughput than that of FP-FIX peer selection strategy. This is due to the fact that when multiple *recipient-peers* try to access the same file from same *source peer* simultaneously, contention occurs on the shared wireless channel in case of *random-peer* and *closest-peer* selection strategy. Our *favorable-peer* selection strategy avoids this problem through judicial selection of *source-peers*. Moreover, in all cases, flex-routed *favorable-peer* method outperforms fixed-routed *favorable-peer* method.

2) *Fairness and aggregate throughput:* Here, we also investigate the effect of fairness constraints on the overall throughput of WMN. Fig. 2 shows the relationship between fairness and aggregate throughput of the network. For α-fair utility functions, a widely accepted notion that the larger α is the more fair. With the maximization objective function ($\alpha = 0$), the simulation results shows that the throughput is maximum for all peer selection strategies. Without fairness constraints, maximum network efficiency in terms of aggregate throughput is achieved at the expense of starvation of some peers. With the increase of α, aggregate throughput decreases from highest value (maximization problem) to the lowest value (max-min problem). For large value of $\alpha(= 10)$ (close to max-min fairness), the throughput is minimum for all peer selection strategies at the expense of fairness. E2E rate of the peers are made as equal as possible to the smallest E2E rate providing highest degree of fairness. Also, the proportional fairness scheme ($\alpha = 1$) allocates higher E2E rate for peers with better channel condition while maintaining minimum E2E for all peers. This method ensures some degree of fairness avoiding starvation to any peer provided. Hence, there exists a trade-off between the total throughput of the network and fairness in WMNs.

VI. Conclusion

We have developed an optimization framework to maximize the utility of a P2P system over WMNs through favorable peer selection. We have solved the optimization problem employing penalty-based GA and thereby quantified the upper bound of the aggregate throughput. The results provides an understanding of the determining factors behind network performance such as the degree of matching between the P2P overlay and its underlying physical network, the effective routing scheme, and nonetheless optimal peer selection. With *favorable-peer* selection strategy, network-wide load-distribution and minimum interference are achieved even with smaller degree of replication. Specially, when any *recipient-peer* discovers multiple source-peers, throughput can be increased dramatically upon intelligent selection of peers among the *source-peers*. We also have shown that there exists a critical relationship between the fairness and the achievable aggregate throughput of the network. Designing distributed P2P protocol in WMNs that captures this notion is our ongoing future work.

References

[1] S.-J. Kim, X. Wang, and M. Madihian, “Cross-layer design of wireless multihop backhaul networks with multiantenna beamforming,” *IEEE Trans. Mobile Comput.*, vol. 6, no. 11, pp. 1259–1269, Nov. 2007.

[2] P. Soldati and M. Johansson, “Network-wide resource optimization of wireless OFDMA mesh networks with multiple radios,” in *Proc. IEEE International Conference on Communications (ICC)*, June 2007, pp. 4979–4984.

[3] J. Tang, G. Xue, and W. Zhang, “Cross-layer design for End-to-End throughput and fairness enhancement in multi-channel wireless mesh networks,” *IEEE Trans. Wireless Commun.*, vol. 6, no. 10, pp. 3482–3486, Oct. 2007.

[4] J. Li, L. Huang, W. Jia, M. Xiao, and P. Du, “An efficient implementation of file sharing systems on the basis of WiMAX and Wi-Fi,” in *Proc. IEEE International Conference on Mobile Adhoc and Sensor Systems*, Oct. 2006, pp. 819–824.

[5] C.-M. Huang, T.-H. Hsu, and M.-F. Hsu, “Network-aware P2P file sharing over the wireless mobile networks,” *IEEE J. Sel. Areas Commun.*, vol. 25, no. 1, pp. 204–210, Jan. 2007.

[6] S. M. ElRakabawy and C. Lindemann, “Peer-to-peer file transfer in wireless mesh networks,” in *Proc. Wireless on Demand Network System and Services (WONS)*, 2007, pp. 114–121.

[7] M. Mehrjoo, S. Moazeni, and X. Shen, “An interior point penalty method for utility maximization problems in OFDMA networks,” in *Proc. IEEE International Conference on Communications (ICC)*, 2009, pp. 1–5.

[8] M. Wall, “GAlib: A C++ library of genetic algorithm components,” *Mechanical Engineering Department, Massachusetts Institute of Technology*, 1996.