Distributed Topology Control with SINR Based Interference for Multihop Wireless Networks

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Abstract. In this paper, a distributed approach to topology control (TC) is proposed where the network topology is established considering interference and routing constraints. This optimization problem however involves link scheduling and power assignment under SINR constraint, which is an NP hard problem. Opting for heuristics rather than exact approach, the proposed algorithms in the literature, either cannot guarantee the quality of the solution, or approximate the interference (protocol interference model) rather than using realistic SINR models. There is also lack of distributed exact/approximation approaches which can reduce complexity and provide practical solutions. Here, we propose a distributed approximation algorithm using column generation (CG) with knapsack transformation on the SINR constraint. Particle Swarm Optimization (PSO) is integrated with CG, to provide robust initial feasible patterns. The results show that, DCG-PSO with knapsack transformation increase the solvable instances three fold in terms of number of nodes, in comparison to the state-of-art approaches. The links are scheduled with less power, shorter scheduling lengths and reduces the computation time at lower penalty cost.

Keywords: Topology control · Scheduling · SINR · Approximation · Distributed

1 Introduction

Wireless Multihop networks have wide range of application in todays world [1,2] such as the military field communication and hot-spots for daily use. These networks can be deployed independently or can also co-exist with fixed infrastructure. Thus forming an integral part of the structure for future networks, which is considered a large dynamic mesh network. While the application of such networks is increasing with the advent of new applications, the three fundamental aspects: energy efficiency, connectivity and receiver centric interference mitigation are becoming more and more important. In order to address these fundamental challenges many solutions have been proposed in the literature, such as, power aware MAC layers [3] and location based routing for connectivity [4]. Despite the considerable amount of work in these directions, the proposed approaches not only increase the complexity of the layers but are also not able to accommodate

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effectively all three fundamental challenges. Here we have considered topology control (TC) [1,2]. TC addresses these challenges on the link layer level and reduces the complexity of other layers such as MAC and routing layer. Generally, TC mainly comprises of power control [5] and/or scheduling [6,8] at the link layer. Here, we have considered scheduling with power control to implement the optimization framework. The proposed approach is a distributed approximation algorithm, providing fault tolerance, energy efficiency and mitigating interference. The interference is based on SINR rather than protocol model thus giving a realistic measurement of interference [9,11,12] and fault tolerance is attained by subjecting to the explicit k-vertex connectivity constraint [10,15], that connects each node to k other nodes. Here, the complexity of finding the solution is due to the SINR constraint which makes the problem NP complete [7,13]. While the maximum number of nodes cannot exceed six in order to find the optimal solution with SINR constraint [14], the approximation approaches in literature are also confined to a maximum of 18 to 30 links [19,20]. In most cases, either the SINR approximations such as node degree [13] or protocol model are used or the heuristics are opted instead of exact solutions. Although heuristic approaches offer less computation time and larger solvable instances than exact solutions, unlike the optimal (exact) approaches, heuristics cannot guarantee the quality of the solution: that is to remain within upper and lower bounds. On the other hand, the approximation approaches offer better overall solutions, by adhering to the lower or upper bound by a constant or dependent factor. s Here, mixed integer linear programming (MILP) is used with distributed CG method [16]. All the transmitters run the distributed algorithm simultaneously while utilizing the local information only. Depending on the network a centralized entity can provide the global information however the algorithm can run without it too. The proposed method provides a distributed topology with links offering minimum scheduling length with power control for Spatial Time Division Multiple Access (STDMA) multihop networks. In summary, our main contributions are as follows.

- We present a novel MILP formulation to minimize the scheduling length and total power of the network under routing, power and k connectivity constraints.
- A novel distributed approximation algorithm based on CG, DCG-PSO is proposed, where we transform the SINR constraint to knapsack problem and solve the pricing problem in two stages, which reduces the complexity of the problem. The feasible link set is increased and interference set is decreased while the upper and lower bounds are made efficient in each iteration.
- As CG performance is influenced by the initialization, instead to random initialization which may effect the stabilization of CG, we integrate distributed Particle Swarm Optimization (DPSO) to provide better initial feasible solutions.

The proposed DCG-PSO results in a 5 times increase in the number of nodes than the state of the art [18,19], less computation time and better solutions.

The resulting topology consists of links with less scheduling length, less power consumption and more spatial reuse. The DCG-PSO is the first approximation algorithm to the best of our knowledge that can solve up to 80 nodes, while supporting simultaneously k-connectivity, minimum transmit power and receiver centric interference mitigation.

The rest of the paper is organized as follows. At first, the network model is explained in Sect. 2. In Sect. 3, the formulation of optimization framework and algorithm is illustrated. The evaluation and results are given in Sect. 4, followed by conclusions in the Sect. 5.

2 Network Model

We consider a multihop STDMA wireless network consisting of N nodes with $(i, j)\varepsilon L$ directed links. The free space model is used for the channel gain G_{ij} calculation. The $G_{ij} = \varphi.d_{ij}^{-\alpha}$ where, d_{ij} is the distance between two nodes i and j, α is the path loss exponent and φ is the uniform random perturbation. P^i is the power of a node i while the value of the power can be continuous or integer value. The following formulation can be applied to CSMA given the respective changes are made in formulation.

2.1 Feasible Access Patterns

The feasible pattern is a subset of links transmitting simultaneously subjected to the given constraints. Here, for the links L in the network, a set of links $S \subseteq L$ that are simultaneously active such that no links share a node is called matching. If the links in a matching S are concurrently activated such that the minimum SINR requirement is met, then such a matching is called feasible matching or pattern. Here, the minimum SINR requirement, i.e given the SINR is provided by (1), the links within a matching satisfy the specified SINR threshold. In (1), γ is the SINR threshold and n_o is the noise The SINR threshold can be different for each link, here for simplicity purposes we have assumed same threshold for all links.

$$\frac{P_i G_{ij}}{n_o + \sum_{j,i \neq m}(P_m G_{jm})} \geq \gamma \tag{1}$$

The power of a link needs to be high enough to meet the minimum k connectivity and data rate requirement such that QoS does not get effected. Scheduling can be defined in a number of ways. Here, schedule Q is the index collection such that $Q = (S^q, \tau^q, q\epsilon Q_I)$, the scheduling length is measured in terms of number of slots as well as total duration in seconds. The length of schedule is $\tau^q \geq 0$, and represents the duration in the matching S, while $Q_I \subseteq Z^+$ is a large and finite set. The traffic demand vector is f_{ij} for the link *(i,j)* and is given in mbps. Each transmission frame length is divided into slots $q\epsilon Q_I$ and the within each slot the matching is active for the duration τ^q. The given demand is completely transferred in the frame length.

The flow conservation balance is the multihop routing constraint here. Flow conservation is applied per session $c \epsilon C$, where one session c comprises of a source, a destination and the demand. In the demand flow constraint, the f_{ij}^{c} is the demand flow for link i, j and session c. The $f_{i}^{c} = k$ when i node is the origin of session c, $f_{i}^{c} = -k$ if i is destination of c and zero otherwise. It means all the relaying nodes have $f_{i}^{c} = 0$.

3 Optimization Framework

3.1 Centralized Algorithm: Column Generation (CG)

The centralized algorithm is based on CG, it takes global information about the network into account and executes centralized knapsack algorithm for the formulation. The CG comprises of a master and a pricing problem, and it reduces the complexity of the problem by focusing on the variables that can have potential in improving the existing solution. CG is an iterative approach where it attempts to search for reduced cost variables in each iteration. In order to do so, the master problem (MP) solves its constraints and passes the dual variable to the pricing problem (PP) which comprises of constraints with exponential complexity. If a variable with reduced cost is found it is added to the optimal solution. The following is the MP formulation.

$$minimize \sum_{1 \leq q \leq |Q|} \tau^{q} \tag{2}$$

subjected to:

$$\sum_{j \epsilon N} f_{ji}^{c} - \sum_{i \epsilon N} f_{ij}^{c} = f_{i}^{c} \tag{3}$$

$$\sum_{i \epsilon N} f_{ij}^{c} \leq 1 \tag{4}$$

$$f_{ij}^{c} \epsilon (0, 1) \tag{5}$$

$$\sum_{1 \leq q \leq |Q|} u_{ij} \tau^{q} \geq \; f_{ij} \tag{6}$$

$$\tau^{q} > 0 \tag{7}$$

Here, the master problem of CG consists of the flow conservation constraint with the objective function of minimizing the scheduling length. The flow conservation and disjointed node is ensured by (3) and (4) respectively. The capacity constraint is (6) where u_{ij} is the Shannons capacity. Among all possible feasible solutions of an optimization problem, only a subset of such solutions/variables, known as basic variables participate in getting the optimal solution while the rest of non-basic variables can be discarded. The master problem (MP) is thus transformed into a restricted master problem (RMP) which considers a subset of initial feasible scheduling patterns. The set of all possible feasible matching is Q while its subset is $Y \subseteq Q$. The RMP consisting of (8)(9) and (3-5)(7) is provided below.

$$minimize \sum_{q \epsilon Y} \tau^q \tag{8}$$

subjected to:

Constraints (3),(4),(5),(7)

$$\sum_{q \epsilon Y} u_{ij} \tau^q \geq \ f_{ij} \tag{9}$$

3.2 Distributed Algorithm

The CG as described above is a centralized approach thus providing solution based on global information. Such techniques can result in high computational complexity and significant overhead. In order to provide a solution which can be implemented in small to large multi hop networks here we provide the distributed approach for CG. Although every node is capable to decide on the local information only, however in the presence of a centralized entity such as access points in mesh networks or base stations in case of multi hop cellular networks the global information is used for better efficiency. The distributed RMP (same formulation as centralized RMP), takes into account the local information and runs at each transmission node simultaneously. While the pricing problem is executed as per individual nodes situation. The pricing problem (PP) from (10)–(16) consists of mainly the constraints with exponential complexity, which is the SINR constraint here. The objective of the PP is to maximize the reduced cost and upon finding a reduced cost, the new pattern is added to RMP to contribute in finding the optimal solution.

$$maximize_{(i,j) \epsilon E} u_{ij} v_{ij} x_{ij} \tag{10}$$

subjected to:

$$P_i G_{ij} x_{ij} + M(x_{ij} - 1) - \gamma \sum_{j, i \neq m} (P_m G_{jm} x_{jm}) \geq \gamma n_o \tag{11}$$

$$\sum_{i \epsilon N} x_{ij} + \sum_{j \neq i, j \epsilon N} x_{ji} \leq 1 \tag{12}$$

$$x_{ij} \epsilon (0, 1) \tag{13}$$

$$0 \leq P_i \leq P_{max} i \epsilon N \tag{14}$$

$$\sum_{i \epsilon N} x_i \leq k - 1 \tag{15}$$

$$x_i \epsilon (0, 1) \tag{16}$$

The objective of PP is (10), where v_{ij} is the dual variable of the constraint (9) in RMP that is provided to PP. The inequality in (11) is the SINR constraint where M is a large integer which linearises the constraint. This method is known as Big M method. The constraint (12) ensures that each node either transmits or receives at a time, here x_{ij} is a decision variable representing an edge such that $x_{ij} = 1$ if link (i, j) is active, otherwise $x_{ij} = 0$. The k connectivity constraint (15) is ensuring minimum of $k - 1$ links to provide fault tolerance.

In case of power control, P_i also becomes the decision variable with an additional constraint on the values of power (14). These constraints on the value of power depends on the nature of value i.e. continuous or integer. The M is a large integer which linearises the SINR constraint, this method is known as the 'big M approach. However in an attempt to calculate an individual value for each link, here the value of M is taken as:

$$M_{ij} = \gamma \left(\eta_o + \sum_{m \neq i,j} P_m G_m j \right) \tag{17}$$

The distributed algorithm is executed at all transmitters simultaneously.

3.3 SINR Transformation

Although the big M approach makes unnecessary constraints redundant, its values are not optimized, as it introduces numerical discrepancy in linear formulation. Here, we first transform the explicit SINR constraint to knapsack problem. This allows minimization of the time required to reach the convergence point and avoids the numerical complexity related to M. The generalized form of a knapsack problem with objective (18) and constraint (19) is as under:

$$maximize \sum_{i \epsilon N} a_i x_i \tag{18}$$

subjected to:

$$\sum_{i \epsilon N} c_i x_i \leq B \tag{19}$$

Such that x_i can have binary or finite integer range. The a_i is profitable cost while c_i is the weight and B is simply a constraint constant. Given that link (i, j) is active, upon applying the knapsack transformation, the SINR constraint can be represented as following.

$$P_i G_{ij} - \gamma \sum_{j,i \neq m} (P_m G_{jm} x_{jm}) \geq \gamma \eta_o \tag{20}$$

$$\sum_{j,i \neq m} (P_m G_{jm} x_{jm}) \leq P_i G_{ij} / \gamma - \eta_o \tag{21}$$

Here, $i, j \epsilon N$. If, we take $P_m G_{jm} = c_{jm}$ and $P_i G_{ij} / \gamma - \eta_o = B$ then by taking $u_{ij} = a_{ij}$, we can transform PP to knapsack. Here, the transformation to knapsack simplifies the problem as it eliminates the explicit SINR constraints (11) removes the numerical discrepancies induced by big M method and represents the problem at hand as set cover. The set cover removes the unnecessary constraints and converges towards the optimal more effectively.

3.4 Algorithm Description

The algorithm starts by running RMP problem and call the algorithm for pricing problem in each iteration. Here in RMP algorithm, at first the transmitting node broadcasts its power and data demand. After establishing the neighbourhood information, PSO provides initial feasible patterns Y and power values P_i. The RMP problem is solved by each transmitting node simultaneously and the dual variable v_{ij} associated with each link is then provided to PP. The algorithm for PP returns the new column variable and power values. This loop run till the cost $u_{ij}v_{ij} \leq 1$. The pricing problem is solved by two main sub-functions such that end results impacts the bounds and optimal feasible results. For the PP algorithm the dual of primal formulation is considered. As, the dual of the knapsack problem is the covering problem, so by transforming the primal pricing problem with knapsack constraint as stated above is converted to covering problem. Here, the vertex set is formed based on the nodes in violation of SINR. The number of nodes in the interference set is decreased by adjusting the power and allowing the subsets of links that can be tolerated for simultaneously transmission. As a result the cardinality of interference set and feasible set decreases and increases respectively. The optimal k connectivity is calculated. The vertex cover number serves as the high priority to SINR and allow to choose optimal k per node where $k \geq 2$. The final scheduled links form the network topology where the link is removed as its demand is met and new links are added. Traditionally, the topology control is triggered when a link vanishes or added, here the link demand is the main criteria.

3.5 Initial Feasible Solutions: DPSO

CG is usually initialized by a set of feasible solution/pattern which is taken as a single link in the network. As the performance of CG is significantly influenced by the initial settings, here distributed particle swarm optimization (DPSO) is chosen to provide better initial feasible pattern and initial power levels. It not only provides various patterns but also reduces the number of iterations to provide stable solution. The DPSO is executed by each transmitter and in take only the local information. The formulation of DPSO involves defining the particle of the population, velocity and position update technique. Here, the particles represent nodes in the network, while forming a matrix that represents the power allocated to each node forms. If we represent the particle as $x_{i,j}$, where $(i,j)\epsilon L$, then $v^t_{i,j}$ and $d^t_{i,j}$ is the particle's velocity and distance at iteration t. The local and global best are calculated, represented as $x^{lo}_{i,j}$ and $x^*_{i,j}$ respectively. The velocity and position update equations are provided here. In the formulation below, $\varsigma_{soc}\epsilon R^{+}$ and $\varsigma_{cog}\epsilon R^{+}$ are acceleration coefficients for social and cognition effect while $w_{in}\epsilon[0,1]$ is the inertia coefficient that controls the velocity.

$$v_{i,j}^{t+1} = w_{in}v_{i,j}^{t} + \varsigma_{soc}(x_{i,j}^{lo} - d_{i,j}^{t}) + \varsigma_{cog}(x_{i,j}^{*} - d_{i,j}^{t}) \tag{22}$$

$$x_{i,j}^{t+1} = v_{i,j}^{t+1} + d_{i,j}^{t} \tag{23}$$

4 Evaluation and Results

In this section, we evaluate the efficiency of the proposed optimization framework which provided additional insights on topology control. Here, we have used MATLAB, together with CPLEX 12.5v as an optimal LP solver. The nodes are uniformly distributed, forming an initial random topology and the weight of the link G_{ij} is calculated where $\alpha = 3$ and $\vartheta = [0.8, 1.2]$. The values for k is $[2, |N| - 1]$) here, although the values can be used within the $2 \leq k \leq 20$ range. The SINR threshold is set to 10, noise is set at $10^{(-6)}$ and the maximum power is 0.1 Watts. Here, none of the links share a common node as stated in Sect. 2. The STDMA based network with varying number of nodes from 5 till 80 nodes are taken into consideration. In total of 5 instances of each network size are considered and 250 monte carlo simulation are run for the results.

4.1 Approximation Solution

In this section, we discuss the performance of proposed DCG-PSO knapsack algorithm in terms of average transmission length in terms of number of slots as well as total length in seconds. This discussion is followed by the analysis of the approach with and without power control, computational complexity and then the system level analysis of the algorithm in comparison to similar state of the art techniques. First we determine the minimum transmission length needed to fulfil a given traffic demand over the links. The transmission length is calculated in terms og number of slots, however, the transmission length in seconds can be calculated. At first the proposed distributed algorithm DCG-PSO is compared with centralized version CG-PSO in Fig. 1. As the Fig. 1 shows that the distributed approach provides transmission length with almost a constant gap from the centralized approach. It is observed that the gap can increase slightly at higher number of links, due to the fact that accumulative interference in presence of multicast scenario can increases thus requiring more number of slots to fulfil the traffic demand.

The comparison of DCG-PSO in terms of average transmission length with state of the art is shown in Fig. 2. In this comparison the probing based algorithm [17], ϵ bounded approach [18] and CG distributed based approach in [19] is compared to DCG-PSO. The transmission length provided by DCG-PSO is very low. While the transmission length provided by probing is the largest, the rest of the approaches computed almost the results as DCG-PSO. However all the approaches except DCG-PSO cannot compute for higher number of links. It is

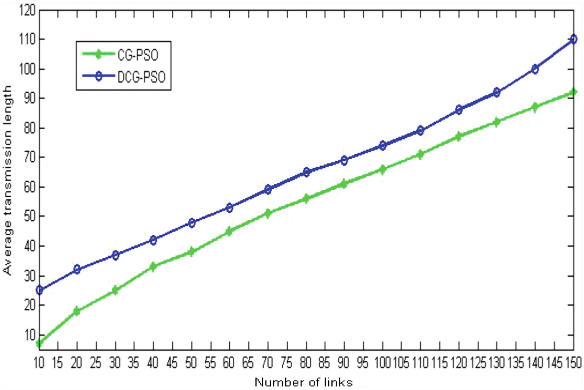
[ht]  s

Fig. 1. Average transmission length by centralized and distributed algorithm

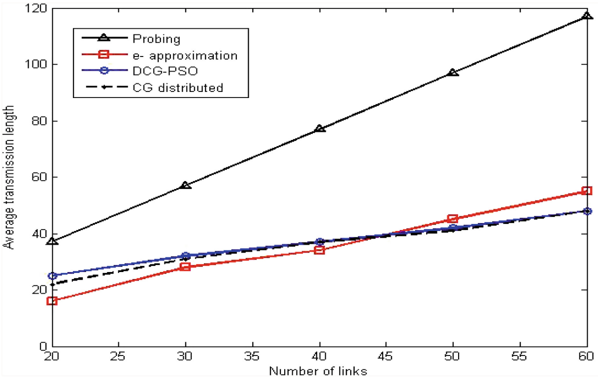
[ht] 

Fig. 2. Comparison of proposed distributed algorithm in terms of average transmission length with state of the art

due to the exponentially increasing computational complexity in terms of run time and number of iterations to converge. In order to compare the convergence, the number of iterations required by each algorithm is illustrated in Fig. 3. The number of iterations is highest in case of [19] while other approaches cannot find convergence at relatively higher number of links as illustrated in Table 2.

The spatial reuse is one in case of TDMA which means only one link is activate in one time slot, in case of STDMA spatial reuse can be greater than or equal to one. The analysis and comparison of DCG-PSO with centralized approach shows that relatively less power is needed while improving the spatial reuse as shown in Fig. 4. The comparison shows that spatial reuse is much closer to centralized approach when distributed algorithm (DCG-PSO) with power control is executed. The increasing spatial reuse is because the total sum of power of the network decreases significantly in case of power control and less power is needed as the number of nodes increases, resulting in increase in simultaneous

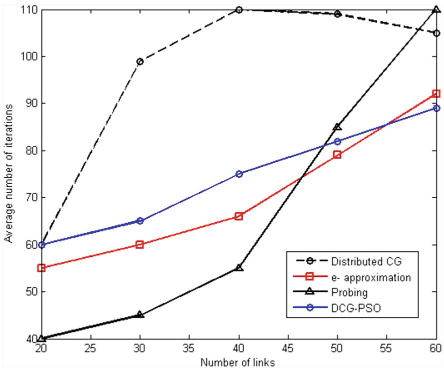
[ht] 

Fig. 3. Comparison of number of iterations of proposed distributed algorithm DCG-PSO and state of the art

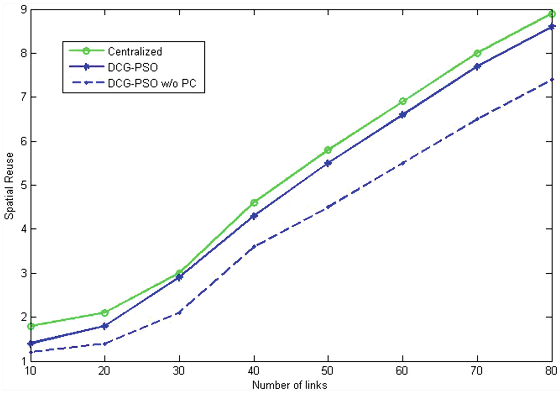
[ht] 

Fig. 4. Spatial Reuse of proposed centralized and distributed approach with and without power control

activation of the links. However, the power control formulation has higher run time and is significant if the density of node is relatively higher, as illustrated in Table 1. This is because, the power control formulation involves extra decision variables and spares networks usually need higher power for connectivity while having larger margin to avoid interference. In Table 1, the average computational time is illustrated for solving a network of 25 nodes and total of 250 instances are simulated. In the Table 2 below the total power of the network for DCG-PSO in comparison to state of the art is provided.

As our CG procedure is initialized by particle swarm instead of greedy and/or single link configuration, the number of iterations to attain the objective value has been reduced and better objective values are obtained. This is due to the fact that CG is sensitive to initial values which can then affect algorithm stability upon each iteration. The average percentage cost penalty, which is defined as

Table 1. Column generation objective values and run time

Technique	Average computational time	Solved instances
DCG-PSO	21.1 s	245
DCG-PSO w/o PC	11 s	248
ϵ- approximation	200 s	180
Distributed CG	587 s	178
Probing	11.12 s	239

Table 2. Total power of the network by DCG-PSO, ϵ approximation and distributed CG approaches

No. of Nodes	Avg. No. of Links	DCG-PSO w/o PC	DCG-PSO w PC	e approximation	CG distributed
10	18	45.0	32.50	31.4	59.40
30	87	82.51	60.90	62.41	No solution found
50	280	502.95	410.61	No solution found	No solution found
80	650	731.52	698.01	No solution found	No solution found

the difference between the optimal O_{opt} and the findings of the algorithm O_{algo}, that is: $(O_{algo} - O_{opt})/O_{opt}$, reduces as the bounding interval and reduced in range. The penalty cost of DCG-PSO is 20 percent at most in worse case. This reduction is due to PSO based initialization and the knapsack transformation, which allows for solving the pricing problem through solving inequalities. The cost penalty also shows that: with increasing search space, the greedy based approach tends to have higher cost penalty than PSO based. The lower bound of RMP is calculated by finding the dual variables di and vijof constraint (3) and (9) If D is a traffic demand vector for the links in Y and optimal value is z then $LB = di.D/1 - z$. The upper bound is also calculated at each iteration, thus contributing into fast convergence.

5 Conclusion

We have considered the problem of network topology based on minimum scheduling length with power control for STDMA multihop network, subject to SINR based interference. We opted for distributed approximation algorithm based on CG. The SINR constraint is transformed such that it reduces complexity. Thus DCG-PSO can solve larger instances, that is at least three fold increase in solvable instances in terms of number of nodes as compared to literature. DCG-PSO provide network topology with shorter scheduling length and minimum power consumption, it has a profound effect on spatial reuse and has minimum penalty cost. Thus, to the best of our knowledge DCG-PSO is the first approximation algorithm to provide the solution for 80 nodes while considering SINR,

k-connectivity and power consumption. The evaluation of proposed algorithm with realistic propagation models, CSMA, effect on throughput and routing is part of our future work.

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