On the Optimal Number of Chargers in Battery-Less Wirelessly Powered Sensor Networks

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***Abstract*—A major advantage of wirelessly powered devices is the use of wire-free and sometimes battery-free nodes that can operate for extremely long times. However, to extend or even to achieve infinite network lifetime a set of chargers is needed to periodically transmit energy to the nodes through the emission of RF signals. In this paper, we study the problem of finding the optimal number of chargers so that a group of nodes can operate without using power sources other than wireless charging. We show that this problem is equivalent to the set-cover problem which is NP-Complete. We propose an efficient heuristic that bypasses the high computational cost of finding the overlapping segments of the harvesting sensor disks and we compare this heuristic to other optimal and non-optimal set-cover solutions. The results show significant performance gains in terms of execution time while keeping the number of chargers close to the optimal value.**

I. Introduction

The new industrial revolution has as its basis the use of hundreds of tiny wireless devices that can sense or control their environment. These sensors not only have limited power resources since they are usually powered by batteries but very often they are also deployed in inaccessible places. The deployments with sensors powered by a permanent power supply suffer from complex cabling systems and very limited mobility.

To alleviate the energy demands of the sensors and comfort the cabling problems, the use of energy harvesting techniques have been recently proposed [1]. Unlike other power harvesting methods (solar, vibration etc.), RF-power harvesting can recharge multiple devices at the same time, thus decreasing even more the amount of needed cabling and easing the network maintenance.

The energy transfer in RF-power harvesting is achieved either by taking advantage of the ambient RF signals transmitted by nearby primary devices or by dedicated chargers that continuously transmit fake data aiming at recharging the nodes. Ambient harvesting has the advantage that it does not require any additional equipment, however, the amount of harvested power varies over time and is much lower compared to dedicated chargers [2].

In this paper, we consider battery-less sensors with energy storage provided by super-capacitors. The super-capacitors are periodically recharged by dedicated chargers and they can provide enough energy to the nodes to operate until the next recharge [3], [4]. However, finding the optimal number and positions of the chargers is a critical problem for maximizing the network lifetime and for reducing the operating costs. For these reasons, we introduce the Optimal Number of Chargers (ONC) problem for deployments with battery-free nodes and we show that it is equivalent to the set-cover problem which is NP-Complete.

To solve the ONC problem we propose an efficient heuristic with low complexity. Unlike state-of-the-art set-cover approaches, our solution bypasses the costly computation of the overlapping areas of the sensor harvesting disks. It creates a graph based on the maximum harvesting distance of the nodes and computes the maximum clique of the graph. Simulation results confirm the lower computation cost of the approach.

The rest of the paper is organized as follows. In Section II we describe the energy consumption and harvesting models and we introduce the ONC problem. Section III describes the proposed solution and Section IV presents the comparison and evaluation results. Section V is dedicated to the related work and, finally, Section VI concludes the paper and presents directions of future work.

II. The optimal number of chargers problem

A. Preliminaries

We split the transmission time in rounds where each round has two phases. During the first phase the nodes get recharged by fake data transmissions of the chargers. The duration of this phase depends on the energy needs of the sensors during the second phase. In the second phase, the nodes transmit their sensing data to the sink spending some of the energy stored in their super-capacitors. Another portion of energy is spent for sensing and other operations. During these two main operations the node remains in active mode. The rest of the energy is used to keep the nodes alive while not transmitting, i.e. when the nodes are in sleep mode.

We adopt the same communication model with [5], where each round is divided in slots. During the first phase the chargers simultaneously transmit fake data while in the second phase we allow only one transmission per slot to avoid interference. Since the data packet rate of the nodes is fixed, we can predict the amount of energy a node consumes during a round and, thus, we can predict the desired duration of the chargers fake data emission.

The energy a node consumes depends on the sensing cost, on how many packets it transmits, and on the amount of time the node remains in active or sleep mode. The nodes take measurements periodically and generate data of size D. The data is encapsulated in a packet of size p bits and it is transmitted to the sink. A node can transmit k packets per round which lasts τ time units. The energy spent for transmitting (per bit) is $\alpha + \beta d^{2b}$, where α is the energy/bit consumed by the transmitter electronics, β accounts for the energy dissipated in the transmit op-amp, and b is the amplitude loss exponent [6].

The total energy cost of a node i per round is C_i^τ.

$$C_i^\tau = (\alpha+\beta d_i^{2b})\frac{k \cdot p}{dr}+De_s+P_{act}t_{act}+P_{rst}t_{act}+P_{slp}(\tau-t_{act}), \tag{1}$$

where dr is the transmission data rate, e_s is the sensing cost per bit, P_{act} and P_{slp} are the power costs while remaining in active and sleep mode respectively. P_{rst} is a fixed power cost for the rest of operations (processing, storage etc.). Note that in this paper we assume that t_{act} is fixed since the nodes generate the same amount of data per round.

We adopt the energy harvesting model proposed in [5] where the energy harvested by a node i in time t while it is in the harvesting range of a charger j is given by (2):

$$H_i^t = \int_0^{t \leq \tau} P_{rx}^{d_{ij}} f^{d_{ij}} \frac{pk_e}{dr} dt, \tag{2}$$

where $P_{rx}^{d_{ij}}$ is the received power, $f^{d_{ij}}$ is the efficiency of the harvesting antenna at distance d_{ij}[1], and k_e is the number of fake packets transmitted per time period. A node may harvest energy using multiple chargers, however, since the harvesting power attenuates considerably with the distance, we assume that the power source can be provided by (the closest) single charger.

The received power at distance d is given by the following propagation model [7]:

$$P_{rx}^d = P_0 \frac{e^{2\sigma G}}{(\frac{d}{\rho})^{2b}}, \tag{3}$$

where $e^{2\sigma G}$ has a log-normal distribution with a shadowing coefficient σ ($G \sim N(0,1)$). The term $1/(\frac{d}{\rho})^{2b}$ accounts for the far-field path loss with distance d, where the amplitude loss exponent b is environment-dependent. P_0 is the received power at reference distance (i.e., ρ).

Due to the discharge properties of the super-capacitors, some of the harvested energy is lost. We define this energy loss as a function of the time between two successive recharges $l_i^t = \lambda H_i^t$, where λ is the power loss factor ($0 < \lambda < 1$).

B. Problem formulation

Given a set of sensors $S = \{s_1, s_2, ..., s_n\}$, we formulate the ONC problem as a minimization problem of the number of chargers N so that the energy consumption per round for each node in S is at least equal to the energy the node harvests for the same period of time minus the energy losses:

$$\min N : C_i^\tau \leq H_i^t - l_i^t \ \forall\ i \in S. \tag{4}$$

Next, we will show that the ONC problem is equivalent to the set cover problem which is NP-Complete.

[1]we use the model provided by the manufacturer Powercast (http://www.powercastco.com)

We set A_i the disk with center the coordinates of node i and range the maximum distance a charger can be placed away from i such that $C_i^\tau = H_i^\tau - l(\tau)$. A_i may overlap with one or more other disks in the network constructing overlapping segment areas of different size.

The overlapping areas create a mosaic of m segments each of them covered by one or more sensors. Each segment area j corresponds to a set O_j containing the sensors covering this particular area. m sets are created with $m \geq n$, $\min|O_j| = 1$, and $\max|O_j| = n, \min|O_j| = 1\ j \in [1, m]$. $|\cdot|$ describes the cardinality of set $\cdot$. An example with 7 nodes and 13 segment areas is presented in Figure 1, where $O_A = \{2\}, O_B = \{1, 2\}$, $O_C = \{1, 2, 3\}$, $O_D = \{2, 3\}$, $O_E = \{1, 3\}$, $O_F = \{1\}$, $O_G = \{3\}$, $O_H = \{4\}$, $O_I = \{6\}$, $O_J = \{6, 7\}$, $O_K = \{7\}$, $O_L = \{1, 5\}$, and $O_M = \{5\}$.

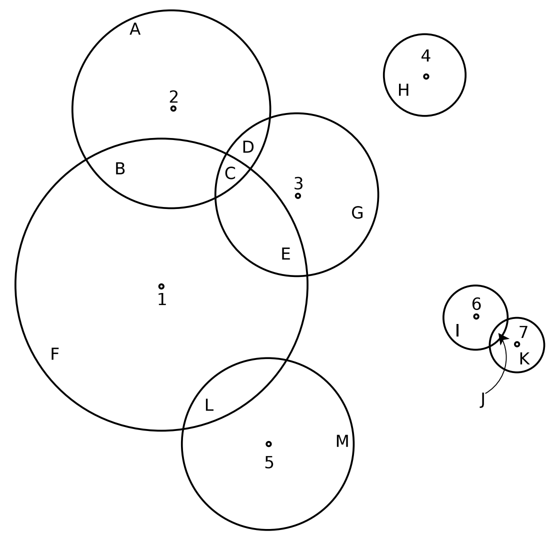

Fig. 1. An example with 7 nodes (numbers), their disks, and the segment areas (letters).

The ONC problem is transformed to a problem of computing the set $O = \{O_1 ... O_\xi\}$ with the minimum possible cardinality ξ such that every sensor in S exists in at least one subset in O.

Thus, given sets O_j, ONC is equivalent to the set-cover problem.

III. The multiple maximum clique heuristic

In this section, we propose a fast heuristic to solve the ONC problem. Since our problem is equivalent to the set-cover problem, the first thought is to use a fast greedy approach to solve the equivalent corresponding problem. However, this would require the computation of the segment areas, a problem which has complexity $\mathcal{O}(n^3)$ [8].

To avoid the high computation cost of the segment areas we propose the Multiple Maximum Clique Heuristic (MMCH). MMCH constructs a unit disk graph $G(V, E)$, where V contains the nodes in S, while two nodes $i, j, i \neq j$ are connected with an edge if the distance between each other is lower than the sum of the ranges of their disks. G requires at most $\frac{n(n+1)}{2}$ computations to be constructed.

Algorithm 1: MMCH

require: G
1 $N = 0$;
2 $\mathcal{C} = \emptyset$;
3 **foreach** $v \in V$ **do**
4   **if** $degree_v == 0$ **then**
5         $G := G \setminus \{v\}$;
6         $N := N + 1$;
7         $\mathcal{C} := \mathcal{C} \oplus \{v\}$;
8   **end**
9 **end**
10 $G_{tmp} := G$;
11 **while** $|V| > 0$ **do**
12     $q :=$ `false`;
13   **while** $q ==$ *`false`* **do**
14   compute the maximum clique Q in G_{tmp};
15   **if** *there is common intersection point of the disks of all sensors in* Q **then**
16             $q :=$ `true`;
17   **end**
18   **else**
19   remove from G_{tmp} the vertices whose disks do not overlap with the most covered segment area in Q;
20   remove from G_{tmp} any other non-member vertex of Q;
21   **end**
22   **end**
23     $G := G_{tmp}$;
24   **foreach** $v \in Q$ **do**
25         $G := G \setminus \{v\}$;
26   **end**
27     $N := N + 1$;
28     $\mathcal{C} := \mathcal{C} \oplus Q$;
29 **end**
30 **return** $(N, \mathcal{C})$;

In the first step of MMCH (see algorithm 1) the algorithm removes from G the nodes with zero degree. These are nodes whose disks do not overlap with any other disk in the network. A number of chargers equal to the number of these nodes is added to N. For the rest of the nodes in G, MMCH uses a number of successive maximum clique computations in order to find the most covered segment areas in the network.

The rational of the maximum clique is the following. If the disks of a number of sensors intersect then these nodes belong to a clique with clique number equal to the number of sensors [9]. The most covered segment area in the network is a maximum clique in G. However, the reverse statement does not always hold; that is if a number of sensors belong to a clique, their disks do not always intersect with each other. MMCH computes the maximum clique of a copy graph G_{tmp} and stores the nodes in set Q. To check if the sensors in Q intersect, Helly's theorem [8] is used with minimum and maximum computational complexity $\Omega(1)$ and $\mathcal{O}(|Q|^3)$ respectively ($|Q| \leq n$). If the disks intersect, the nodes in Q are excluded from future computations and G is updated. If not, the vertices whose disks do not overlap with the most covered segment area in Q are removed from G_{tmp} and Q is recomputed. To lower the complexity of an eventual re-computation of the maximum clique, all other vertices not included in Q are also removed from G_{tmp}. The initial graph G is restored after the computation of the final maximum clique. The algorithm terminates by returning the collection of subsets $\mathcal{C}$ and its cardinality N.

The loop of lines 11-22 ensures that all the nodes in S will be included in a subset in $\mathcal{C}$. If more than one maximum clique of same size exist in G the algorithm selects one randomly. Since G is reduced after every clique computation, some nodes may have zero degree. If no clique is found, the algorithm will randomly select a node with zero degree.

The complexity of MMCH mainly depends on the computation cost of the maximum clique which can be computed fast for sparse and large graphs like those of 2 or 3-dimensional networks [10]. We note that cliques can be computed in polynomial time when the geometric representation is provided [9]. We must, also, note that the `While` loop of lines 13-21 is executed at most two times with maximum cost $\mathcal{O}(|Q|^3 + |Q - \iota|^3)$, where ι the number of conflicting nodes. The lower computation bound is $\Omega(1)$.

The possible charger positions computed by MMCH are infinite, lying within the borders of the corresponding segment areas. However, this position can be optimized in order to reduce the operating costs (e.g., electricity cost). `OptimalSearch()` is a subroutine which approximates the optimal position of each charger by exhaustively searching a segment area. The optimal position is defined as the position where the total harvesting energy of the nodes in a subset in $\mathcal{C}$ is maximized. The approximation factor of `OptimalSearch()` is ϵ, where ϵ is a user-given value. Finally, the range of each individual charger can be adjusted based on the furthest node in its vicinity.

IV. Evaluation & discussion of the results

A. Setup

We assume a scenario with a fixed size square terrain of 25 meters side and a variable number of nodes randomly and uniformly scattered on the terrain. We compare MMCH to a state-of-the-art fast greedy algorithm that solves the corresponding set-cover problem [11] and to an integer linear programming (ILP) set-cover solution that uses the GLPK[2] library to optimally solve the problem instances. We measure the minimum number of chargers as well as the execution time of the three approaches. Due to the presence of random values, we run each instance 10 times and the average results are presented. The 95% confidence intervals are also displayed.

Regarding the node and charger characteristics, we consider the following values: $p = 127bytes$, $D = 256bits$, $dr = 250Kbps$, $k = 1$ packet per round, $k_e = 150$ packets/sec (unless specified), $\tau = 30$ seconds, $\sigma = 0.1$, $P_0 = 10mW$, $\rho = 1m$, $\alpha = 50nJ$, $\beta = 100pJ$, and $b = 1$. We, also,

[2]https://www.gnu.org/software/glpk/

Procedure OptimalSearch(V, ϵ)

```
require: a subset V in C, ε
compute μ: the sensor with the shortest range in the
  subset;
U_max := 0;
fp := (0, 0);
for i = 0; i ≤ x_μ + r_μ; i = i + ε do
    for j = 0; j ≤ y_μ + r_μ; j = j + ε do
        c := 1;
        foreach s ∈ V do
            if distance to (i, j) ≥ r_s then
                c := 0;
            end
        end
        if c == 1 then
            U := 0;
            foreach s ∈ V do
                U = U + H_s;
            end
            if U > U_max then
                U_max := U;
                fp := (i, j);
            end
        end
    end
end
return fp;
```

consider 10% energy loss between recharges ($\lambda = 0.1$). We assume Zigbee communication characteristics operating at 915MHz. Regarding the charger and the harvesting efficiency we used the values provided by Powercast corporation for the P2110B model[3] operating at the same frequency. k, k_e and the node densities are chosen so that no interference exists between the chargers and the nodes (assuming that each node allocates a single slot in each round). The sink is placed in the middle of the left side of the terrain. The algorithms were developed using the Perl programming language whereas the experiments were carried out on an Intel Core2 Duo 1.67GHz CPU with 4GB RAM running Linux. No parallel processing was performed.

B. Results

Figure 2 depicts the results for a scenario with a variable number of nodes and a fixed fake data rate 100 packets/sec. MMCH produces a higher number of chargers but close to the optimal solution. The greedy approach results are similar to the ones achieved by MMCH. On the other hand, the execution times of the LP and Greedy algortithms are higher especially when many nodes are deployed. The higher computation cost of the two approaches is due to the high complexity of the integrated routine that computes the disk overlappings. MMCH postpones or even skips this initial computation to a later phase involving a smaller number of nodes and reduced complexity.

[3]A simulator was developed to approximate the manufacturer's values: http://ulr.gforge.inria.fr/

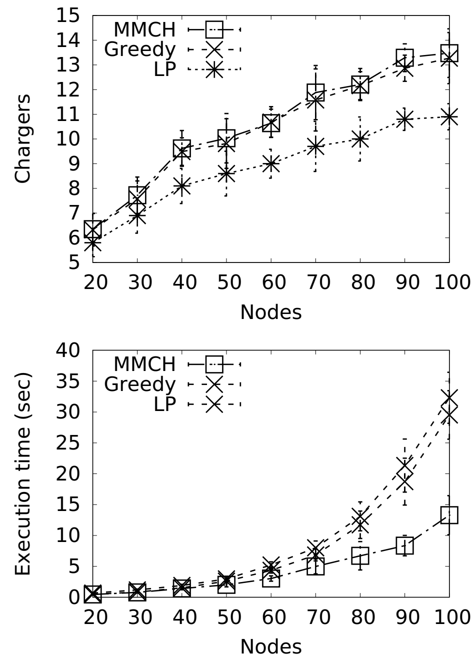

Fig. 2. Number of chargers (upper) and execution time (lower) for a scenario with $k_e = 100$ packets/sec.

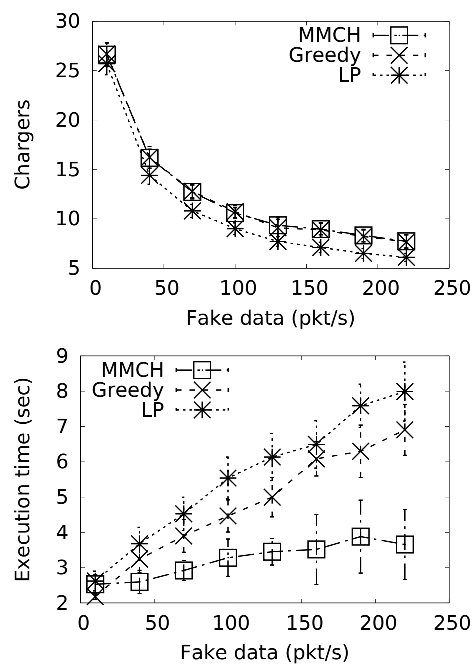

Fig. 3. Number of chargers (upper) and execution time (lower) for a scenario with 60 sensors.

In the next experiment we assess the impact of the fake data packet rate (i.e., k_e) on the number of chargers and on the execution time. In fact, this packet rate affects the time a charger transfers energy to the nodes. The results illustrated in Figure 3 show that the number of chargers is significantly lower as the packet rate increases. The three approaches exhibit results very close to each other. However, in terms of execution time LP presents a linear increase unlike MMCH which depicts a smoother behavior. This increased execution time of the LP and Greedy algortihms is again due to the high computation complexity of finding the overlapping areas that rapidly increases as k_e is getting higher.

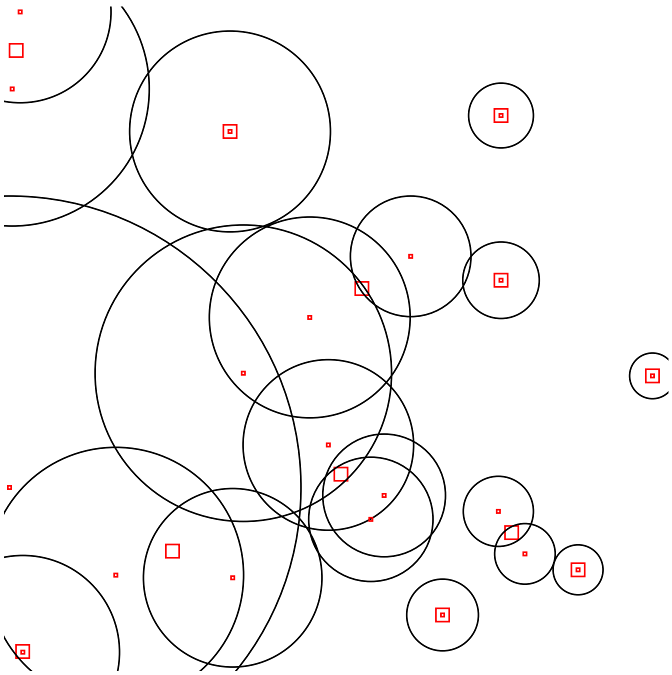

Fig. 4. Solution provided by MMCH for a scenario with 20 nodes and k_e = 20 packets/sec.

Figure 4 shows an MMCH solution with the positions of the chargers (squares), the positions of the nodes (dots), and their corresponding disks (circles). An instance with 20 sensors and $k_e = 20$ packets/sec was used. The algorithm computes 12 charger positions (equal to the optimal value) with 5 chargers covering multiple sensors and 5 chargers covering single sensors. Finally, Figure 5 depicts the evolution of the graph and five maximum cliques computed in every step of the algorithm. Graph G is displayed with green and the maximum clique with bold color within the graph. The five cliques have size 4, 3, 2, 2, and 2, respectively.

V. Related work

Similarly to the current paper, Pang *et al.* examine the problem of finding the optimal number of chargers to replenish the energy of a set of sensors [12]. They propose a partition algorithm to approximate the optimal solution. They prove that their approach has 0.5 probability to achieve the optimal solution. However, no simulation results are given and as it is also mentioned in [13], the harvesting model they used is extremely simplified and not practical.

The charger positioning problem has been recently studied as a problem of maximizing an objective function subject to a power budget [14]. The objective function depends on the maximum consumption of the nodes and the power they harvest for a given deployment. The authors formulate an optimization problem and show that it is NP-Complete. They present approximation algorithms as well as greedy heuristics to find close to the optimal charger positions and their corresponding power transmission levels. The simulation results are close to the optimal and outperform a random placement strategy.

A similar problem is studied in [13]. The authors propose a wireless charger placement problem definition that takes into account the electromagnetic radiation. The solution they propose guarantees that the electromagnetic radiation levels are safe for every location on the plane. The performance of the proposed approximation algorithm is validated through both simulation and experimentation.

The problem of computing the optimal number of readers to cover an area with static or mobile RF-power harvesting RFIDs is studied in [15]. The authors propose an analytical model to determine the optimal distance between the readers. The model is supported by simulation results.

Finally, the problem of optimally placing a charger for clustered wireless sensor networks is tackled in [16]. The feasibility of grouping the nodes in clusters, the maximum size of the cluster, and its network lifetime are examined. Localized as well as centralized solutions are presented to solve the above mentioned problem. Simulation results show that the network lifetime can be extended compared to traditional communication schemes.

VI. Conclusion & Future work

In this paper, we studied the problem of computing the optimal number of chargers for a sensor network consisting of RF-power harvesting and battery-free nodes. We showed that the problem is equivalent to the set-cover problem which is NP-Complete. We proposed a low complexity algorithm based on the maximum clique computation. Simulation results showed that our solution is faster than a state-of-the-art greedy set-cover approach while it does not perform far from the optimal.

In the future, we intend to evaluate the proposed solution using a real experimental environment and assess the impact on the number of chargers of a noisy environment as well as of different packet rates per sensor. Part of our future research is, also, to involve sensors with controlled mobility and compute the minimum number of chargers as well as the optimum exposure path of the nodes based on their energy demands.

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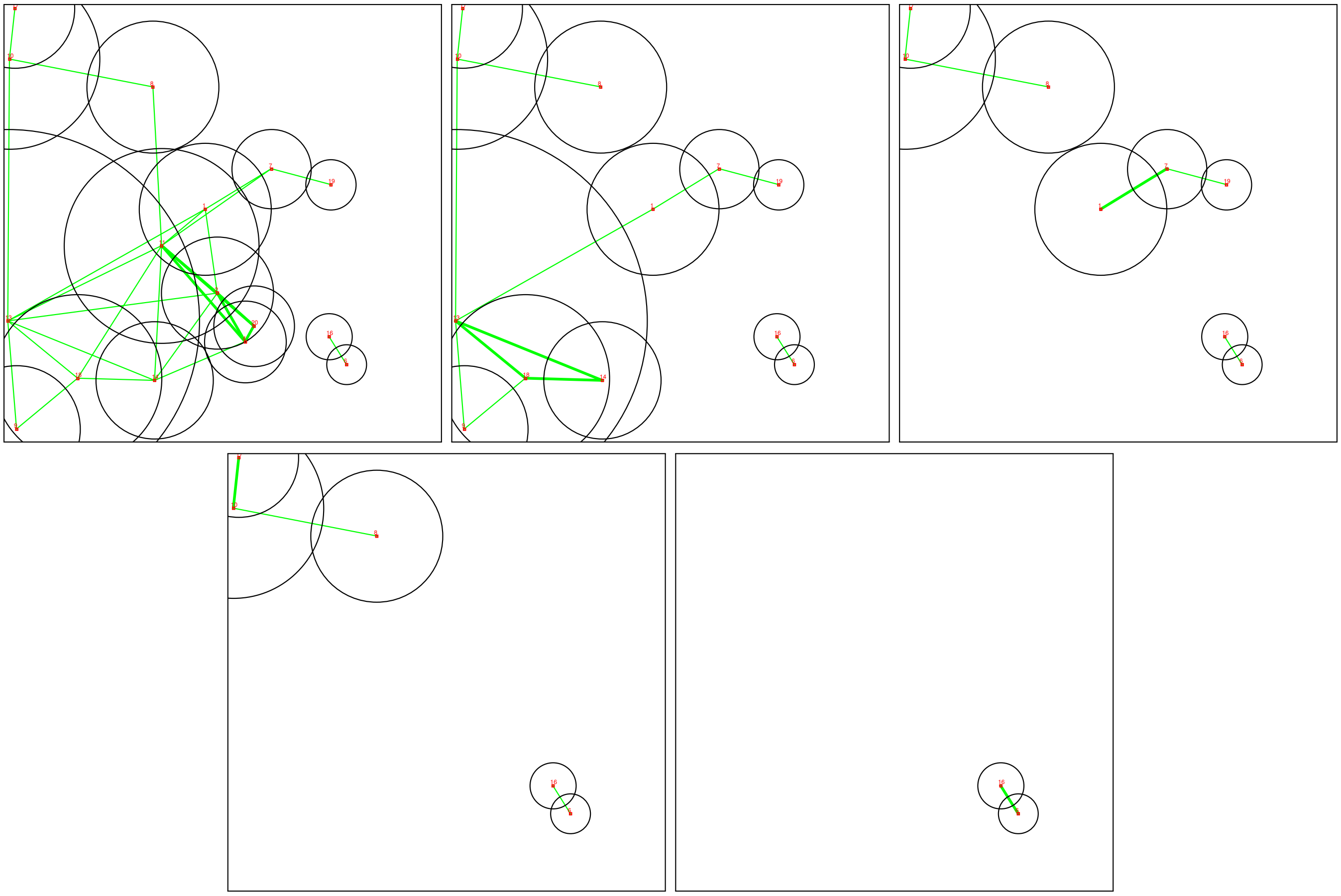

Fig. 5. Graph G (green) as well as the five cliques (bold green) computed by MMCH for a scenario with 20 nodes (dots) and $k_e = 20$ packets/sec.

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