Heuristic Algorithms for Optimization of Energy Consumption in Wireless Access Networks

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Abstract

Energy consumption of wireless access networks is in permanent increase, which necessitates development of more energy-efficient network management approaches. Such management schemes must result with adaptation of network energy consumption in accordance with daily variations in user activity. In this paper, we consider possible energy savings of wireless local area networks (WLANs) through development of a few integer linear programming (ILP) models. Effectiveness of ILP models providing energy-efficient management of network resources have been tested on several WLAN instances of different sizes. To cope with the problem of high computational time characteristic for some ILP models, we further develop several heuristic algorithms that are based on greedy methods and local search. Although heuristics obtains somewhat higher results of energy consumption in comparison with the ones of corresponding ILP models, heuristic algorithms ensures minimization of network energy consumption in an amount of time that is acceptable for practical implementations. This

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confirms that network management algorithms will play a significant role in practical realization of future energy-efficient network management systems.

Keywords: WLAN, energy-efficiency, heuristic algorithm, optimization, green networking

1. Introduction

Power consumption of the Information and Communication Technologies (ICT) sector has become a key issue in the last few years, due to rising energy costs [1][2] and serious environmental impacts on greenhouse gas emissions [3]. Pollution and energy savings are keywords that are becoming more and more of interest to people and governments, and the research community as well are more sensitive towards these topics in the last years. An important part of the ICT consumption, the energy consumption of wireless access networks is rapidly increasing [4] and in some countries it accounts for more than 55% of the whole communication sector [5]. Such increase also accounts to a non-negligible part of the operational expenditures (OPEX) of network equipment owners. Moreover, growth of data rates in wireless networks by a factor of roughly ten every five years and an increase in the number of users, result in a doubling of the energy consumption of wireless network infrastructure every 4–5 years [6].

With rising energy prices, base stations (BSs) as the most significant energy consumer in the wide area wireless access networks contribute up to 50% of the total OPEX, especially if operators have many diesel fueled off-grid BS sites [7]. In addition, the number of enterprise deployments and overall number of individual access points (APs) in small and medium size wireless local area networks (WLANs) increases exponentially every year [8]. Although average BS energy consumption is much higher in comparison to those of APs, vast numbers of WLAN network devices installed worldwide contribute to enlargement of the energy consumption in wireless access networks. Therefore, development of a new generation of wireless access networks characterized with significantly higher energy efficiency is a necessity.

For having “greener” wireless access networks not only requires us to develop more energy-efficient hardware components, but to take a holistic view of the complete wireless access network through implementation of energy-efficient network management. This means that network devices must adopt their on/off state and level of transmitted (Tx) power in accordance with traffic patterns. To achieve this for large-scale wireless networks without hampering coverage and/or client performance, management of network devices activity and Tx power from a centralized location seems to be a promising approach.

But, energy-efficient network management requires appropriate algorithms capable of exploiting minimal network resources at any moment, while assuring to active users satisfactory level of service quality. Therefore, in this paper, we present several versions of heuristic algorithms based on a combination of greedy approach and local search methods. While ensuring at any moment coverage and capacity demands of active users, we embedded in developed algorithms features: line capability of offering full coverage of service area (SA) and limitations in frequent variations of network devices activity. Also, a comparison of obtained results in terms of energy savings and computational time has been performed between heuristic algorithms and equivalent integer linear programming (ILP) models.

The rest of the paper is organized as follows: in Section 2, we present related work dedicated to improving energy efficiency of wireless access networks. Section 3 gives an overview of analyzed network instances and explains approximations of real traffic patterns. Formulation of

ILP models and heuristic algorithms has been presented in Section 4 and Section 5 respectively. Numerical results obtained have been discussed in Section 6 and in Section 7, we give some concluding remarks.

2. Related work

Topics dedicated to reductions of energy consumption in wireless access networks have attracted the attention of the research community very recently. Some initial ideas and results for the case of wide area wireless access networks can be found in [9][10][11][12][13][14] [15], while energy saving approaches in WLANs have been investigated in [16][17][18][19][20][23]. Authors in works [9] and [10] showed that it is possible to switch off some cellular network cells [9] and UMTS Node B’s during low-traffic periods, while still guaranteeing quality of service constraints in terms of blocking probability and electromagnetic exposure limits [10]. The impact of deployment strategies on the power consumption of mobile radio networks considering layouts featuring varying numbers of micro BSs per cell in addition to conventional macro sites has been investigated in [11]. In [12], the authors evaluate the energy savings that can be achieved with the energy-aware cooperative management of the cellular access networks of two operators offering service over the same area. The total and per user power consumption for three different wireless technologies including, namely fixed WiMAX, mobile WiMAX and UMTS, is investigated in paper [13]. In paper [14], the relationship between the energy efficiency and spectrum efficiency in a multi-cellular network is obtained, and the impact of multi-antenna on the energy efficiency of cellular networks is analyzed. Dynamic adjustment of wireless topology and the radiated power using methods such as bandwidth shrinking and cell micro-sleep in accordance to load have been investigated in work [15].

Furthermore, a first attempt for adoption of resource on-demand (RoD) strategies that can reduce energy consumption of centrally managed WLANs was published in a significant work [16]. Authors in [17] develop an analytical model for assessment of the effectiveness of RoD strategy introduced in [16]. The proposed analytical model is used for studying two simple on-demand policies that based on instantaneous WLAN parameters, select the appropriate number of APs to activate, thus trying to avoid wasting energy on underutilized APs. According to both papers [16] and [17], ample room for possible energy savings in large-scale WLANs exists. In article [18] authors propose solutions in the area of energy sustainable WLAN mesh networks through introduction of AP solar powering, also discussing the shortcomings of IEEE 802.11 when used in these types of networks.

In our positioning paper [19], for the first time principles of ILP are used to show possible reductions of instantaneous power consumption in real size WLANs through implementation of energy-efficient network management. We extended obtained results in work [20] through development of new ILP models, indicating significant savings in monthly energy consumption on the level of complete WLANs. Actually, we manage to modulate energy consumption of WLANs according to the realistic traffic pattern, also considering important factors like: full coverage of SA, negative effect of frequent variations on activity of network devices, influence of interference among network elements and capacity limitations of network devices.

Although an optimization approach based on ILP models presents a powerful tool for modeling possible energy savings in wired [21][22] and wireless networks [19][20], the ILP approach is not without drawbacks. Due to NP-hardness of optimization models proposed in our recent work [20], computational time of some ILP models becomes very long. Since long computational time reduces the possibility for practical implementation of ILP models in real-time management systems, in the paper [23] we present an initial version of heuristic algorithm

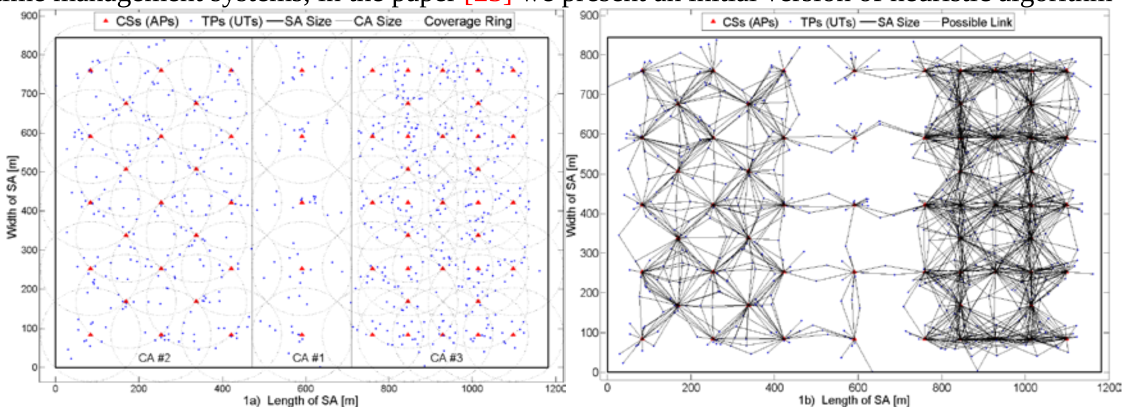
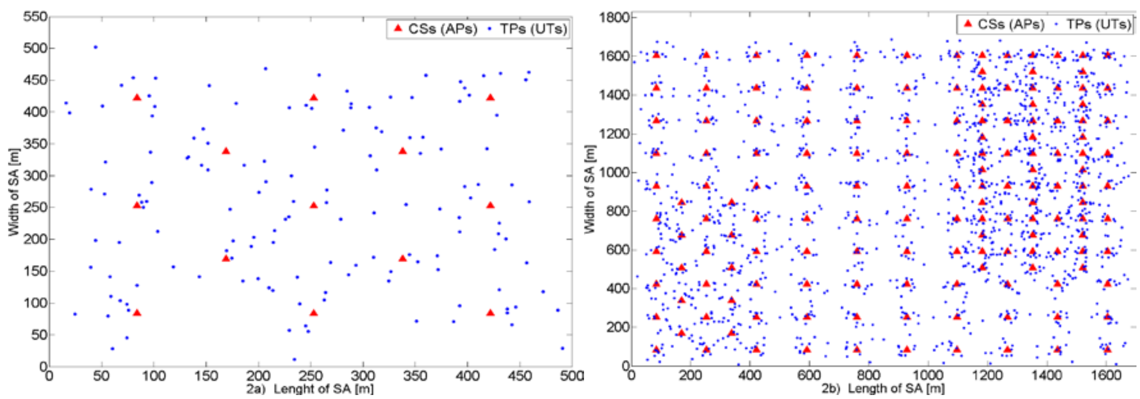


Fig. 1. **a)** Positions of APs and UTs inside medium size network instance, **b)** Possible wireless connections between APs and UTs inside medium size network instance



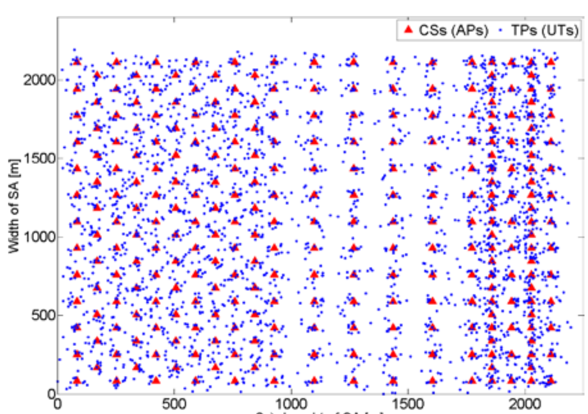


Table 1. Properties of analyzed WLAN instances

Size of network instance	**No. of UTs (TPs)**	**No. of APs (CSs)**	**Dimensions of SA (m x m)**
Small	143	13	506 x 506
Medium	671	61	1.182 x 844
Large	1672	152	1.689 x 1.689
Extra-large	3069	279	2.196 x 2.196

Fig. 2. Allocation of APs and UTs inside: **a)** small, **b)** large and **c)** extra-large network instance

for energy-efficient management of WLAN resources. According to our knowledge, this is the first algorithm for management of on/off activity and Tx power of APs in large-scale WLANs. The development of such an algorithm was a necessity, since all previous research lacks algorithms capable of adapting energy consumption of WLANs to actual traffic load. In order to further improve the management properties of the initially proposed algorithm, we develop in this paper a few extended versions of the heuristic algorithm.

Table 2. Dependence of instantaneous AP power consumptions and PHY rates on level of Tx power

Level of Tx power *k*	**Baseline power consum. P_b (W)**	**Additional power consum. P_k (W)**	**Average power consum. *P(k)* (W)**	**Tx power P_{Tk} (mW/dBm)**	**Distance (coverage rings)**		
					***r*=1 (0 m–40 m)**	***r*=2 (40 m–80 m)**	***r*=3 (80 m–120 m)**
					Average PHY rates		
					R_{jkr} (Mb/s)	**R_{jkr} (Mb/s)**	**R_{jkr} (Mb/s)**
1	5	7	12	100/20	R_{j11}=54	R_{j12}=36	R_{j13}=18
2	5	5	10	75/18,8	R_{j21}=48	R_{j22}=24	R_{j23}=12
3	5	3	8	50/17	R_{j31}=36	R_{j32}=18	R_{j33}=9
4	5	1	6	25/14	R_{j41}=24	R_{j42}=12	R_{j43}=6 (N/A)

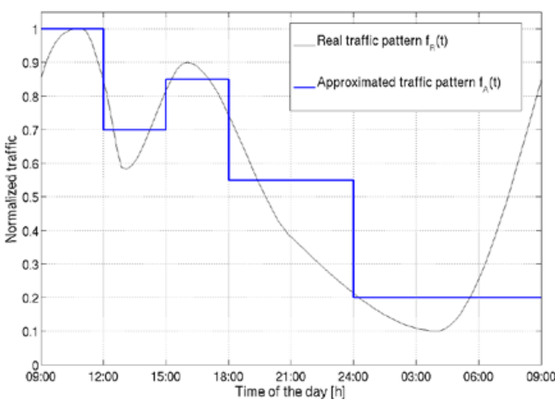


Fig. 3. Approximation of real traffic pattern

Table 3. Time periods for traffic approximation and parameters of path-loss model

Traffic approximation					**Path-loss model values**
Time period *t*	T_t [h]	T_{t+1} [h]	$\Delta T_t = T_{t+1} - T_t$ [h]	% of active users	λ =0,122 m X_σ =6,23 dB d_0=1 m
1	00	09	9	20	*n* = 2,7
2	09	12	3	100	*f*=2,4 GHz
3	12	15	3	70	σ=13 dB
4	15	18	3	85	$\overline{P}_{pl}(d_0) = 40$ dB
5	18	24	6	55	$P_{rtr}(d)$= - 83 dBm

3. Analyzed network instances and traffic patterns

For testing energy management strategies introduced in the paper through ILP models and heuristic algorithms derived later on, we tried to emulate the topology of widespread IEEE 802.11g WLANs. For that purpose we use for analyses four different WLAN network instances, assuming that APs in each instance work in infrastructure mode. As specified in **Table 1**, instances are named as: *small, medium, large and extra-large instances* due to differences in the size of SA and number of APs and user terminals (UTs). Allocation of APs and UTs inside SA of: small, medium, large and extra-large instance have been presented in **Fig. 1-(a)**, **2-(a)**, **2-(b)** and **2-(c)** respectively. Such network instances can correspond to various real WLANs, which deployments can be seen in everyday life. For example, small and medium instances resemble some office or faculty building WLANs, while large and extra-large instances can be identified with WLANs of a travel terminal like train station or airport complex. To be more consistent with real WLAN deployments, we assume that larger network instances have different allocation densities of APs in different coverage areas (CAs), e.g. medium instance has three CAs (**Fig. 1-(a)**). This is similar to real network topologies where generally, a higher number of APs have been allocated inside those CAs where a higher number of UTs is expected.

In order to simulate changes of traffic load during one day, the discrete function $f_A(t)$ presented in **Fig. 3** is used for approximating normalized daily traffic pattern $f_R(t)$ of a realistic WLAN. According to **Table 3** and **Fig. 3**, approximation is done using five different time periods *t*. In the paper [20], we experiment with higher and lower numbers of approximation time periods and we show that selection of five time periods presents the best trade-off between computational accuracy and computational time of ILP models. We additionally assume no time gap between subsequent time periods, also neglecting somewhat unequal traffic patterns between working and weekend days. Durations of time periods are expressed in hours (h) as the time difference between ending (T_{t+1}) and starting time (T_t) of some time period *t*. The percentage of active users in each time period with corresponding durations can be found in **Table 3**.

Generation of network instances presented in **Fig. 1** and **2** have been done using a specially developed software solution written in C++ programming language. Such *instance generator* (IG) performs generation of network instances according to a wide range of initially defined input parameters such as: size of SA, number of network and user devices, guaranteed PHY rates to users, sensitivity threshold, number and duration of time periods, etc. The IG generates data of network instances in the appropriate forms, which are used as input data for CPLEX solver or heuristic algorithm. In order to model radio propagation characteristics of analyzed WLAN instances, IG uses a *long distance path-loss model* with log-normal fading [24][25] defined as

$$P_{pl}(d) = \overline{P_{pl}}(d_0) + 10n\log_{10}\left(\frac{d}{d_0}\right) + X_\sigma \qquad \text{[dB]} \tag{1}$$

where $\overline{P_{pl}}(d_0)$ is the average value of the path loss at close-in reference distance d_0, n is path-loss exponent and X_σ is a zero-mean Gaussian distributed random variable having standard deviation σ. Parameters of the path-loss model used by IG are presented in **Table 3**, and these values correspond to those of real WLANs [24][25]. We assume that a potential wireless link exists between AP and UT located at Euclidean distance *d* from AP, only if the signal strength at the position of UT satisfies the next criteria:

$$P_r(d) = P_{Tk} - P_{pl}(d) \le P_{rtr} \qquad \text{[dBm]} \tag{2}$$

where P_{Tk} is Tx signal strength (in dB) of AP and P_{rtr} is power sensitivity threshold of each UT equal to -83 dBm (**Table 3**). According to these criteria, straight lines on **Fig. 1-(b)** present potential wireless links among APs and UTs of medium size WLAN instance, and similar visualization of potential wireless links can be obtained for other network instances presented in **Fig. 2**.

4. Formulation of optimization models

To formulate the energy optimization problem, we assume that instantaneous (average) power consumption of wireless network devices can be expressed as a function of Tx power (P_{Tk}). If a wireless network device transmits a radio signal with the Tx power P_{Tk}, baseline power consumption P_b increases for amount of P_k resulting in instantaneous consumption equal to

$$P(k) = P_b - P_k \qquad [\text{m}] \qquad (3)$$

Table 2 shows considered values of AP baseline P_b and additional power consumptions P_k for different Tx power levels P_{Tk}. Also, we assume maximal CA of each AP equal to 120 m, which is a typical value for moderately obstructed indoor WLAN environments. Inside the CA of each AP, we considered three circular coverage rings with borders: $0 \le d \le 40$ m, 40 m $< d \le 80$ m and 80 m $< d \le 120$ m. All users located in some coverage ring will have the same PHY rate, which can be treated as the average transmission rate R_{jkr} (Mb/s) of the corresponding CA. **Table 2** presents values of PHY rates in each coverage ring for different Tx power levels. Values are selected according to practical measurements of IEEE 802.11g AP PHY rates [26]. To mathematically model the radio coverage of SA having already deployed APs, we take into account possible positions of UTs called *test points* (TPs) and all positions of the APs called *coverage sites* (CSs). Let:

- $j \in J = \{1, ..., m\}$ be the set of m CSs hosting APs,
- $i \in I = \{1, ..., n\}$ be the set of n TPs where UTs are placed,
- $t \in H = \{1, ..., p\}$ be the set of p different time periods during one day,
- $r \in D = \{1, ..., e\}$ be the set of e coverage rings (areas) around each AP,
- $k \in K = \{1, ..., l\}$ be the set of l different Tx power (P_{Tk}) levels,
- $i \in I(j,k,r,t)$ be the subset of TPs covered with (j, k) combination in r-th coverage ring during time period t.

The problem is to find in each time period t a set of powered-on CSs with minimal power consumption satisfying capacity demand d_{it} (in Mb/s) of all active TPs. Such a problem is a combination of *minimum set covering problem and capacitated facility location problem* and to formulate the problem we introduce three binary decision variables:

$$y_{jt} = \begin{cases} 1 & \text{if an AP is powered-on at } j\text{-th CS} \\ & \text{during time period } t \\ 0 & \text{otherwise} \end{cases}$$

$$x_{jkt} = \begin{cases} 1 & \text{if aditional power } P_k \text{ is consumed by } j\text{-th} \\ & \text{CS during time period } t \\ 0 & \text{otherwise} \end{cases}$$

$$w_{ijkt} = \begin{cases} 1 & \text{if TP } i \text{ is assigned to } j\text{-th CS transmitting} \\ & \text{at } k\text{-th power level during time period } t \\ 0 & \text{otherwise} \end{cases}$$

Furthermore, 0–1 incidence matrix containing coverage information of all TPs is defined as

$$a_{ijk} = \begin{cases} 1 & \text{if TP } i \text{ is covered by CS } j \\ & \text{consuming aditional power } P_k \\ 0 & \text{otherwise} \end{cases}$$

The first ILP optimization model named as *Model Energy* (ME) can be formulated as

$$\text{Min}\left[\sum_t \sum_j P_j y_{jt}(T_{t+1} - T_t) + \sum_t \sum_j \sum_k P_k x_{jkt}(T_{t+1} - T_t)\right] \times C \qquad (4)$$

S.t.

$$\sum_{k} x_{jkt} \leq y_{jt} \qquad \forall (j,t): j \in J = \{1,...,m\},\ t \in H = \{1,..., p\} \tag{5}$$

$$\sum_{j}\sum_{k} a_{ijkt} x_{jkt} \geq 1 \qquad \forall (i,t): i \in I = \{1,...,n\},\ t \in H = \{1,..., p\} \wedge \forall d_{it} \neq 0 : a_{ijkt} \neq 0 \tag{6}$$

$$\sum_{r\in D}\ \sum_{i\in I(j,k,r,t)} \frac{d_{it} w_{ijkt}}{R_{jkr}} \leq 1 \qquad \forall (j,k,t): j \in J = \{1,...,m\},\ k \in K = \{1,...,l\},\ t \in H = \{1,..., p\} \tag{7}$$

$$x_{j_b k_b t} + \sum_{h=b+1}^{B} w_{ij_h k_h t} \leq 1 \qquad \forall (i,t): i \in I = \{1,...,n\},\ t \in H = \{1,..., p\},\ d_{it} \neq 0,\ s.t.\ \forall b: 1 \leq b \leq B-1 \tag{8}$$

$$w_{ij_h k_h t} \leq x_{j_b k_b t} \qquad \forall (i,t): i \in I = \{1,...,n\},\ t \in H = \{1,..., p\},\ d_{it} \neq 0,\ s.t.\ \forall b: 1 \leq b \leq B,\ h = b \tag{9}$$

$$\sum_{h=1}^{B} w_{ij_h k_h t} = 1 \qquad \forall (i,t): i \in I = \{1,...,n\},\ t \in H = \{1,..., p\},\ d_{it} \neq 0,\ h = b \tag{10}$$

$$y_{jt} \in \{0,1\} \qquad \forall j \in J = \{1,...,m\}, \forall t \in H = \{1,..., p\} \tag{11}$$

$$x_{jkt} \in \{0,1\} \qquad \forall j \in J = \{1,...,m\}, \forall k \in K = \{1,...,l\}, \forall t \in H = \{1,..., p\} \tag{12}$$

$$w_{ijkt} \in \{0,1\} \qquad \forall i \in I = \{1,...,n\},\ \forall j \in J = \{1,...,m\}, \forall k \in K = \{1,...,l\}, \forall t \in H = \{1,..., p\} \tag{13}$$

Relation (4) is an *objective function* that minimizes monthly energy consumption of a complete WLAN. Constant C equal to 0.03 (1/month) in the objective function is used for transformation of daily energy consumption (Wh/day) in the monthly energy consumption (kWh/month). We use this unit for expressing the energy consumption of a wireless network, since kilowatt-hour (kWh) is the billing unit preferred by utility companies for charging consumed electrical energy. Constraints (5) are *coherence constraints* stating that each CS (AP) can use at any moment at most one Tx power level. *Coverage constraints* (6) assure that all TPs are within the CA of at least one CS and *connection constraints* (10) states that every TPi can be connected to only one CS at any time. Since total capacity of each powered on CS is shared between connected TP(s), *capacity constraints* (7) prevents that overall TP demand(s) d_{it} in the *r-th* coverage ring exceed PHY rate R_{jkr} of that ring. *Best power selection constraints* (8) make implicit assignment of TPs to the best active CS in terms of the signal strength. According to *configuration constraints* (9), TP i can be assigned to a CS j only if that CS is active and configured with *k-th* transmit power level. Finally, for decision variables y_{jt}, x_{jkt} and w_{ijkt}, constraints (11), (12) and (13) are the *integrality constraints.* All described constraints must be satisfied for each period t.

To mathematically model full coverage of the SA with radio signal during all the day, we introduce a concept of virtual points called measurement points (MPs), where

- $s \in S = \{1, ..., u\}$ is the set of u MPs inside the SA.

The MPs serve as probe points in which minimal level of received signal strength according to relation (2) must be satisfied. With dense allocation of MPs having a regular grid structure, full coverage of the SA can be assumed. By adding to the previous model ME a new constraint

$$\sum_{j}\sum_{k} b_{sjk} x_{jkt} \geq 1 \qquad \forall (s,t): s \in S = \{1,...,u\}, \forall t \in H = \{1,..., p\} \tag{14}$$

results with a new ILP model named as *model energy/full coverage* (ME/FC). Since *full coverage constraints* (14) mandate that every MP be covered with the radio signal received from at least one CS during each time period, those constraints assure complete coverage of the SA.

In addition to presented ILP models, we develop an ILP model that reduces frequent variations in on/off activity of CSs between subsequent time periods. We introduce this model since large variations in network configuration from one time period to the next one may have a negative impact on signaling overheads and perceived service quality. One approach in reducing this impact can be through introduction of an *energy penalty* for powering on a new CS that was turned off in the previous time period. To mathematically express influence of this penalty, we introduce a new binary variable defined as

$$z_{jt+1} = \begin{cases} 1 & if \quad j-th \quad CS \quad is \quad activated \quad in \quad subsequent \quad time \quad period \\ 0 & otherwise \end{cases}$$

A new objective function considering the penalty for powering on CSs in a subsequent time period can be formulated using this binary variable as

$$\text{Min}\left[\sum_{t=1}^{T}\sum_{j} P_j y_{jt}(T_{t+1}-T_t) + \sum_{t=1}^{T}\sum_{j}\sum_{k} P_k x_{jkt}(T_{t+1}-T_t)\right]\times C + \sum_{t=1}^{T-1}\sum_{j} z_{jt+1}E \qquad (15)$$

By substituting objective function (4) of previous models ME and ME/FC with objective function (15) and by adding to the previous constraints (5–13) the new ones defined as

$$z_{jt+1} \geq y_{jt+1} - y_{jt} \qquad \forall(j,t): j \in J = \{1,\ldots,m\}, \forall t \in H = \{1,\ldots,p-1\} \qquad (16)$$

$$z_{jt} \in \{0,1\} \qquad j \in J = \{1,\ldots,m\}, \forall t \in H = \{1,\ldots,p\} \qquad (17)$$

a new mathematical model named as *Model Energy Limited Variations* (MELVs) has been developed. In the objective function (15), E is the value of energy penalty equal to 0.003 kWh/month. For calculation of this value we exploit energy consumed by network device during booting, assuming that powering on of new CS repeats among subsequent time periods for each day during one month. All presented optimization problems belong to the NP-hard category, since each of them includes as a special case the capacitated facility location problem, known to be NP-hard [27].

5. Heuristic algorithms

Another approach for solving the problem of energy-efficient network management is based on development of a heuristic algorithm. Besides exact algorithms for ILP problems like branch and bound, cutting plane, etc. that finds the optimum or at least bounds it, other algorithms like heuristic algorithms only find some (hopefully good) solution. Nevertheless, heuristics are important in practice because efficiency is often a high priority. An efficient heuristic algorithm is the one which determines a solution within a reasonable time using reasonable resources. For the types of problems considered in this work, a typical reasonable time frame is a few hours and a typical reasonable resource is a high-end personal computer (server).

Our heuristic approach has been spatially tight to the problem tackled by previous ILP (mathematical) models, focused on energy consumption minimization of large-scale WLANs. Actually, for each of the proposed ILP models we develop corresponding heuristic algorithms. In this way, we can compare obtained results in terms of computational time and accuracy. Therefore, the first heuristic algorithm named as *Heuristic-Model Energy* (H-ME) works in the same manner as the previously introduced ME, tending to minimize monthly energy consumption of the entire network. The second heuristic algorithm named as *Heuristic-Model*

Energy/Full Coverage (H-ME/FC) optimizes monthly energy consumption while ensuring full coverage of the SA. *Heuristic-Model Energy Limited Variations* (H-MELVs) is the last proposed heuristic algorithm, which as an MELV model offers energy-efficient network management, also limiting frequent variations in the activity of network devices.

Given an instance with a set of CSs, TPs and corresponding traffic demands d_{it} (Mb/s), the aim of each heuristic algorithm is to build up a solution **S** that offers the lowest energy consumption of the network in each time period. During this process, different heuristic algorithms must take into account different constraints, like guaranteeing full SA coverage or limiting frequent on/off changes of network devices. Generally, each of the proposed heuristic algorithms is composed of two phases. In the first one, we adopt a *greedy approach* in order to build up a feasible solution **S**. The greedy is an algorithm that finds the solution (locally optimum) through a sequence of partial decisions, without ever coming back to the taken decisions in order to modify them. Generally, greedy algorithms have high computational efficiency, but they do not assure reaching of the global optimum. *Local search* (LS), instead, is useful to improve the solution of the greedy algorithm, looking inside a neighborhood of the solution. Therefore, in the second phase, LS starts with an initial solution **S** and iteratively moves to a best candidate within the current neighborhood until no further improvement can be achieved. If this happens, we memorize this solution; otherwise we keep the greedy solution.

5.1 Greedy phase

The generic structure of the first H-ME algorithm is:

```
Algorithm: Generic structure of H-ME heuristics
PROCEDURE Heuristic_ME (I,J,K,P)
   S=∅;
BuiltUpSolution (I,J,K,P,S)
LocalSearch (S);
RETURN (S)
END Heuristic_ME
```

where meaning of the sets: I, J, K, and corresponding indexing are the same as the ones introduced in the previous Section. With $\boldsymbol{P}$, we denote for each (j, k) pair, subset of TPs covered with that (j, k) pair. In the $\boldsymbol{P}$**,** for each P_(j, k) combination, TPs are sorted in decreasing order of the signal strength received from that (j, k) combination. Additionally, **S** is the set of (j, k) combinations, with $j \in J$ and $k \in K$, that belongs to a final solution. Therefore, (j, k) combinations in **S** define which CS j transmitting at Tx power level k will be powered on during some time period t.

Each phase of proposed heuristic algorithms is characterized with the related generic function. The *BuiltUpSolution* function in the greedy phase develops, after sequence of iterations, a feasible starting solution *S*. The pseudo code of the greedy phase is:

```
Algorithm: Greedy phase strategy for H-ME heuristics
PROCEDURE BuiltUpSolution_ME (I,J,K,P,S)
      Covered_TPs = ∅;
WHILE Covered_TPs ! = ALL_TPs
      Best_Pair = BestPairselection_ME (J,K,P,S);
      S = S U Best_Pair;
```

```
        Covered_TPs = Covered_TPs U TPs_PairToAdd
      TPs_Association (S,P);
     Try_Decrease_Power (S);
 END BuiltUpSolution_ME
```

At the beginning of the greedy phase, the *BuiltUpSolution* function creates and puts to null the set of all active TPs that are covered with the current solution *S* during time period *t*. Then it invokes the *BestPairSelection* function. This function looks for a (j, k) pair that covers the highest number of active TPs which are not yet served. A pair that satisfies such criteria will be added to the solution *S* at the end of each iteration of the *BuiltUpSolution* function. The pseudo code of the *BestPairSelection* function is:

```
Algorithm: TPs coverage strategy
PROCEDURE BestPairSelection_ME(J,K,P,S)
  DO FOR j in J, k in K
      Capacity_(j,k) = 1;
  Covered_new_TPs_(j,k) = 0;
  DO FOR i in P_(j,k)
     IF Capacity_(j,k)-Demand_(i)/Rate[k][r] > 0
       IF i is not yet covered in S
         Covered_new_TPs_(j,k) = Covered_new_TPs_(j,k)+1;
     Capacity_(j,k) = Capacity_(j,k)-Demand_(i)/Rate[k][r];
        FI
        IF i is already covered in S by the same j
                Capacity_(j,k) = Capacity_(j,k)-Demand_(i)/Rate[k][r];
        FI
        IF i already covered in S by different j
           IF powerRX_i_(j,k) > powerRX_i_(j,k in S)
                Capacity_(j,k) = Capacity_(j,k)-Demand_(i)/Rate[k][r];
          FI
        FI
      FI
    OD
  OD
  SELECT (j,k) that has max (C*Covered_new_TPs_(j,k));
  RETURN  (j,k);
 END BestPairSelection_ME
```

In the first step, the *BestPairSelection* function puts normalized capacity of every (j, k) pair to 1 (maximum) and sets the number of TPs that can be covered by that pair to null. Then, the function explores every possible (j, k) pair and for each pair function calculates the number of currently uncovered TPs. Selection of TPs that can be served by analyzed (j, k) pairs is based on order given by $P\_(j, k)$, since TPs receiving better signal from that (j, k) pair have priority during selection. In order to accept a TP, a (j, k) pair must have enough free capacity to satisfy the capacity demand of the TP that will be covered. We define capacity limitation of (j, k) pair as

$$Capacity\_(j,k) - \left[\frac{Demand(i)}{Rate(k,r)}\right] > 0 \tag{18}$$

where *Demand(i)* corresponds to d_{it} and *Rate(k, r)* to R_{jkr}. Therefore, the *BestPairSelection* function starts to select the first TP in the $P\_(j, k)$. If this TP is not yet covered by another pair in *S* and if this TP can be served without breaking the capacity constraint (18), the function increases the number of covered TPs of the (*j*, *k*) pair by one. Also, the function reduces the remaining capacity for the value of TP demand normalized with the proper PHY rate. After that, the function proceeds to the next TP in *P_*(*j*, *k*), repeating the same check about the possibility of covering that TP.

If CS *j* already covers the TP that belongs to *P_*(*j*, *k*), but with a different power level *k*, the function applies only a reduction of the normalized capacity. On the other hand, if some previous (*j*, *k*) combination already covers a TP, but from the newly analyzed pair that TP receives better signal strength, only an update of the normalized capacity of the new pair has to be done. In that case, an increase in the number of newly covered TPs will not be performed since this TP has been already covered. A reduction of normalized capacity and increase of covered TPs does not happen in the situation when an analyzed TP has been already covered by some (*j*, *k*) combination, from which it receives power that is higher than the power level of the new combination.

Finally, the *BestPairSelection* function selects a (*j*, *k*) pair that maximizes the number of newly covered TPs. The chosen (*j*, *k*) combination is then introduced by the *BuiltUpSolution* function in the solution *S*. Moreover, the algorithm updates the number of covered TPs with those served by the just added (*j*, *k*) pair and verifies does demands of all active TPs in the analyzed time period have been satisfied by added (*j*, *k*) combinations in *S*. If this situation does not occur, the algorithm repeats execution of the *BestPairSelection* function until solution *S* satisfies capacity demands of all TPs active in some time period *t*, through adding at each step a new (*j*, *k*) pair.

When *BuiltUpSolution* adds a new (*j*, *k*) pair in the solution *S*, the algorithm invokes the *TPs_Association* function. This function enables, for every TP in solution *S*, a connection with the (*j*, *k*) pair from which the TP receives the best power. In order to reduce the Tx power of (*j*, *k*) pairs in *S* and to more efficiently explore CSs capacity, the greedy phase ends with the *Try_Decrease_Power* function. This function tries to decrease the selected power level *k*, keeping satisfied the same constraints about capacity (7) and best received power (8). Reasons for introducing this function in the greedy phase can be found in significantly better results obtained in terms of monthly energy savings if the *Try_Decrease_Power* function has been present in the greedy phase. Due to space shortage, pseudo code of the *TPs_Association* and *Try_Decrease_Power* function have not been presented for any proposed heuristic algorithms.

For the case of H-ME/FC algorithm, a generic structure is defined with next pseudo code:

```
Algorithm: Generic structure of ME_FC heuristics
PROCEDURE Heuristic_ME/FC (I,J,K,P)
      S=∅;
   BuiltUpSolution_ME/FC (I,J,K,P,MM,S)
   LocalSearch (S);
   RETURN (S)
END Heuristic_ME/FC
```

where the H-ME/FC algorithm has for the input parameters the same sets that we have described for the previous algorithm H-ME, with the exception of the parameter denoted as *MM*. The *MM* has the same meaning as ***P***, but instead of TPs the *MM* is related to MPs.

Therefore, *MM* defines for every (*j*, *k*) pair, a subset of MPs that are covered with the wireless signal of that (*j*, *k*) pair. The greedy phase of the H_ME/FC algorithm is:

```
Algorithm: Greedy phase strategy for H-ME/FC heuristics
PROCEDURE BuiltUpSolution_ME/FC (I,J,K,P,MM,S)
      Covered_TPs = ∅;
      Covered_MPs = ∅;
  WHILE Covered_TPs!=ALL_TPs || Covered_MPs != ALL_MPs
          Best_Pair = BestPairselection_ME/FC (J,K,P,S);
      S = S U Best_Pair;
      Covered_TPs = Covered_TPs U Tps_PairToAdd
      Covered_MPs = Covered_MPs U MPs_PairToAdd
  TPs_Association (S,P);
  Try_Decrease_Power (S);
END BuiltUpSolution_ME/FC
```

Therefore, the solution created by the *BuiltUpSolution_ME/FC* function has to cover not only all active TPs in the analyzed time period, but also all MPs inside the SA. The function continues to add a new (*j, k*) pair in *S* only if both of these two constraints have been satisfied. For this reason we have an 'OR' (||) operator in the condition deciding about exit from the loop that offers final solution. Similar to the previous H-ME algorithm, the (*j*, *k*) combination added in solution *S* at every algorithm step is selected by the function that is now called *BestPairSelection_ME/FC* function. In order to introduce in this function the possibility to count the number of MPs that are uncovered within *S*, we perform some modification of the previous *BestPairSelection_ME* function. Previously, the *BestPairSelection_ME* function selects, among all not yet chosen (*j*, *k*) pairs, the one which has the maximum increment of TPs not covered within solution *S*. The new function calculates for every (*j*, *k*) pair the number of uncovered TPs, also considering the number of uncovered MPs. In order to perform this, we need to memorize at every step which MPs are already covered in solution S. This operation is simpler than the check made for TPs. This is a consequence of the fact according to which MPs do not have to satisfy capacity and best power selection constraints. The algorithm needs to guarantee that all MPs in the final solution *S* have been covered with wireless signal during each time period.

Although the H-MELV algorithm needs to penalize powering on of new CS in subsequent time periods, the generic structure of its greedy phase is equal to those of the H-ME algorithm. Therefore, H-MELV starts with time period one (t=1) and calculates the solution *S* (t=1). Then it calculates solution *S* for time period two (t=2), comparing the previous solution with this last one. The process is performed for each pair of solutions *S* that belong to subsequent time periods. This comparison is done since the H-MELV algorithm must introduce a mechanism of penalty that prefers selection of those CSs that are already active in the previous time period. To do this, the value of quantity denoted as *C* that equals to 1 in the *BuiltUpSolution* function of the H-ME algorithm must be adopted for the case of H-MELV heuristics.

Actually, selection of the (*j*, *k*) pairs performed by the *BestPairSelection_MELV* function is similar to the *BestPairSelection_ME*. When all (*j*, *k*) combinations that are not in *S* have information about the number of uncovered TPs that can be served by each pair (*Covered_new_TPs_(j,k)*), the *BestPairSelection_MELV* function selects the (*j*, *k*) combination having the highest number of uncovered TPs. Before this selection, *BestPairSelection_MELV* multiplies *Covered_new_TPs_(j,k)* with a quantity *C*. The value of this quantity depends on the appearance of the CS *j* in the solution *S* of the previous time period. In this way, it is possible to privilege those (*j*, *k*) pairs to have powered on CS throughout time periods. The appropriate value of quantity c equals to 0,6–0,8 for the cases of already powered CS in the previous time period. On the other hand, for those CSs that are not powered on in the previous time period, the selected value of quantity c equals to 0,3–0,4. Those values of c are selected since an experiences obtained during multiple testing of heuristics shows best results for exactly those values.

5.2 Local search phase

During the second phase, the *LocalSearch* (LS) function is used to improve the feasible starting solution *S* obtained at the end of the greedy phase. The LS starts from an initial solution *S* and moves to a better solution in its neighborhood until it finds a local optimum, i.e., a solution that does not have a better neighbor. A neighborhood is simply a set of solutions that are found by applying an appropriate transformation (move) to the current solution. In other words, LS chooses an initial solution *S* and searches for a set *S'* in solution space *Q(S)* with f(*S'*)<f*(S)*. If none exists, LS stops and *S* is a local optimum solution. Otherwise it sets S=S' and repeats the described search. We have indicated with *S'* a set of (*j*, *k*) pair(s) that are developed from *S* through addition of a CS that is neighbor to existing CS *j* in *S*, and through removal of this CS *j*. Solution space *Q(S)* is the set of all possible neighborhoods so that *Q(S)={S':S'=S* U {*j*} for *j* in *J\S*}U{*S':S'=S*\{*i*} for *i* in *S*}. In our case, a neighbor(s) of a CS in the solution *S* are those CS(s) that are able to cover at least some parts of that CS CA.

The group of all possible neighbors for every CS is calculated before the LS phase and is denoted with ***N***. For every CS *j*, the subset of all possible neighbors has been indicated as *N(j)*. The pseudo code of the LS is:

Algorithm: Common LS strategy for each of heuristic approaches

```
PROCEDURE LocalSearch(S,N,K)
  DO FOR j in S
  Counter=0;
    DO FOR jj in N(j) until Counter<NearMax
     DO FOR k in K
           G(S) = S\{(j,k):j=j}U{(jj,k)}
        S' = BuiltUpSolution_LS(G(S));
        IF S' feasible
     IF Energy_Consump (S')<Energy_Consump(S)
             S = S';
             TPs_Association(S);
           FI
           ELSE
             QUIT FOR k
          FI
       OD
       Counter=Counter+1;
    OD
  OD
 END Local_Search
```

As input, the LS takes the previous solution *S* obtained at the end of the *BuiltUpSolution* function, the set of all possible neighbors ***N*** and the set of power levels *K.* At the beginning, LS selects for every CS *j* in *S* a neighbor and removes the corresponding CS from the solution S. Since such move has changed the previous solution and the possible association with TPs, it is necessary to update connections and to check if a feasible and better solution *S'* can be achieved by selecting (*j, k)* pairs from *G(S)*. With *G(S)*, we indicate the subset of all possible (*j*, *k*) pairs generated starting from *S*, on which a described move can be applied. *G(S)* is generally different from *S'*, because at this point, we do not know which (*j*, *k*) pair will be included in *S'*, what Tx power level the newly-added CS will have and if this solution will be feasible.

To generate *S'*, LS assigns to the added neighbor the highest power level and invokes the *BuiltUpSolution_LS* function. This function is very similar to previously described *BuiltUpSolution* functions. The only difference between them can be found in the way *BuiltUpSolution_LS* selects (*j*, *k*) combinations when it creates *S'*. Instead of choosing among all possible (*j*, *k*) pairs, the *BestPairSelection_LS* function explores only (*j, k*) pairs inside *G(S)*. Every time the algorithm needs to calculate solution *S'* from *G(S)*, it has to satisfy the traffic demand of TPs for the case of H-ME and H-MELV heuristics and also coverage of all MPs for H-ME/FC scenarios.

If a generated solution *S'* is unfeasible or if selected (*j, k*) pairs in *S'* can satisfied the traffic demand of active TPs, but with a higher energy consumption than (*j*, *k*) pairs in S, solution S' will be discarded. Otherwise, if the solution *S'* is feasible and results with lower energy consumption in comparison with energy consumption of *S*, the algorithm memorizes these newly discovered (*j*, *k*) pairs. In addition, the *TPs_Association(S)* function algorithm tries to achieve further improvement in minimization of energy consumption through reduction of Tx power level for the added neighbor until the minimal level of Tx power for this CS can be reached. At that point, LS stops the construction of a new solution, memorizes the recently found (*j*, *k*) configuration and repeats this search for every CS inside the set of neighbors. Once LS reaches the last member of the neighbor set *N(j)*, it generates the final solution for the selected time period and the heuristics proceed with finding a solution for another time period until all time periods have been analyzed.

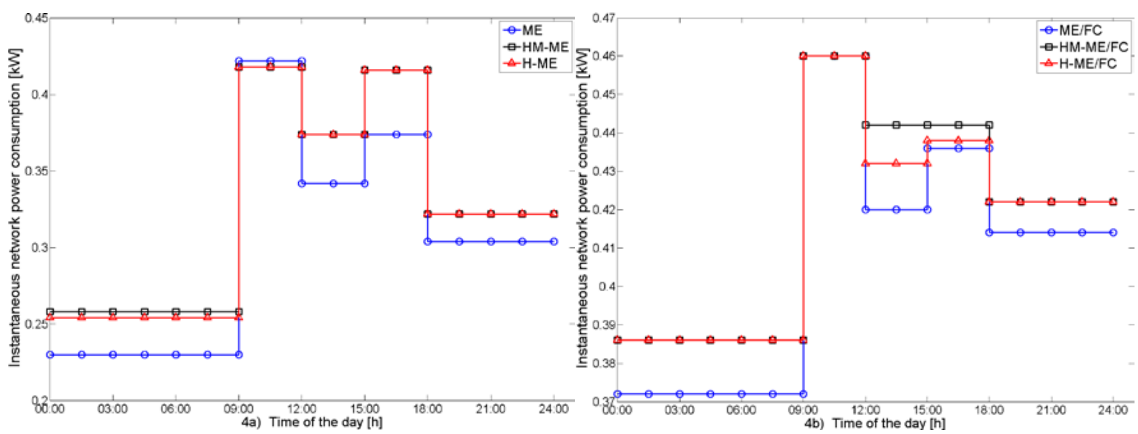
Besides the presented heuristic approaches, we experiment with some additional modifications related to each of the derived heuristic algorithms. These result with development of *modified versions* of heuristics denoted as *Heuristic Modified-Model Energy* (HM-ME), *Heuristic Modified-Model Energy/Full Coverage* (HM-ME/FC) and *Heuristic Modified-Model Energy Limited Variations* (HM-MELVs). Generally, the greedy phase of modified heuristics is the same as of corresponding heuristic models which are previously presented in Section 5.1. When compared with previously presented heuristics, modified heuristics differ in the way of performing selection of neighbor CSs during the LS phase. Instead of analyzing for every CS in *S*, all possible neighbors that are not members of *S*, the LS algorithm of modified heuristics randomly selects only one neighbor for every CS in *S*. This ensures significant reductions in exploration complexity of the LS phase, which in addition influences on the computational time.

6. Numerical results

In order to verify the effectiveness of proposed heuristic algorithms, we have compared results of heuristic algorithms with optimization results obtained by corresponding ILP models. While results of the ILP models have been obtained at the output of CPLEX solver, results of the heuristics approaches are generated following phases of the previously described pseudo codes. The efficiency of heuristic algorithms has been tested using an INTEL-Core 2 E8400 processor with Kubuntu 8.04 OS and its integrated gpp as compiler. To perform an estimation of energy savings obtained with ILP models and heuristic algorithms, we consider the typical working activity of nowadays energy inefficient WLANs. Hence, we assume that every AP (CS) always transmits at maximum Tx power (k=1) and this transmission does not depend on variations in the traffic pattern. Because of this, a permanent average power consumption equal to 12 W (8,64 kWh/monthly) for every CS inside the SA is considered. This is typical average power consumption of APs installed worldwide during last 10 years. Energy consumed by such a network is treated as reference network energy consumption.

6.1 Power consumption and energy savings

For the case of the medium size network instance presented in **Fig. 1**, obtained numerical results in terms of the instantaneous network power consumption and coefficient of energy savings are shown in **Fig. 4**. Coefficient of energy savings have been calculated in accordance with reference to energy consumption of corresponding WLAN instances. The energy savings coefficient for each time period is defined as the ratio of energy consumed by analyzed model and reference energy consumption of analyzed instance. In **Fig. 4** it can be noticed that developed heuristic algorithms can modulate instantaneous network power consumption and energy savings coefficient in accordance with the realistic traffic patterns. **Fig. 4-(b)** reports results of



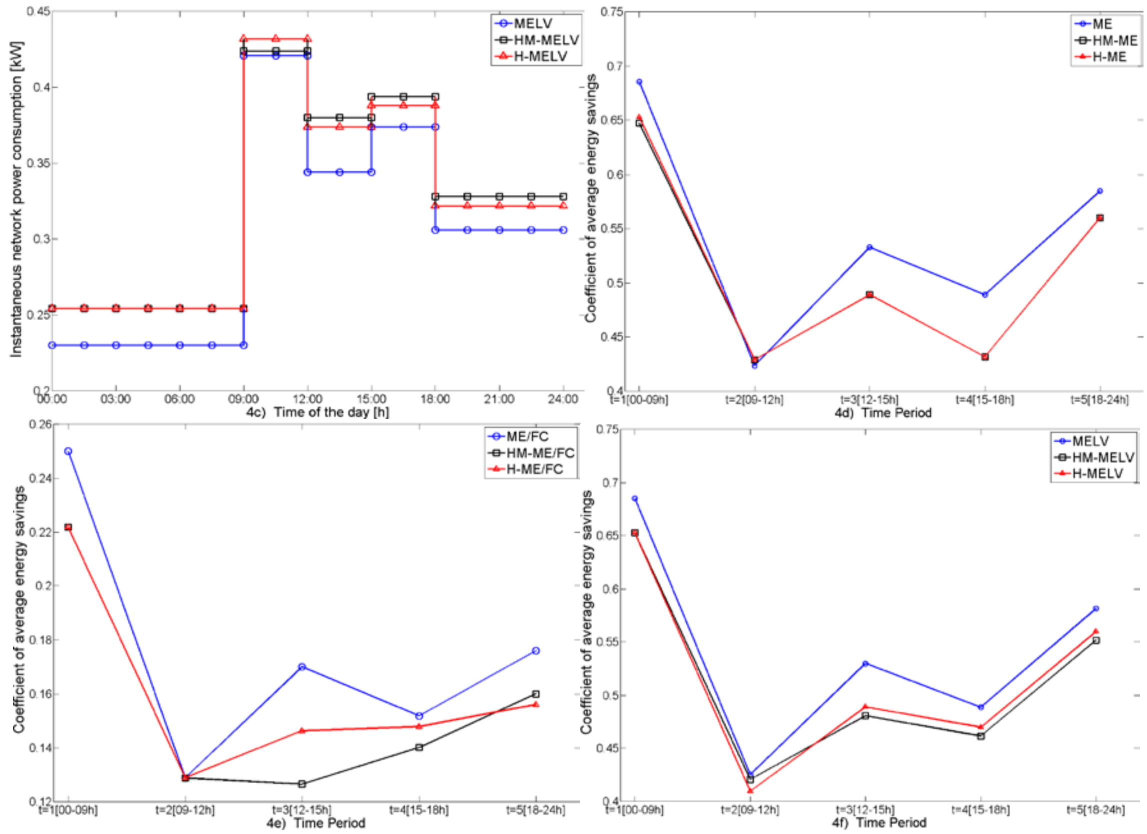


Fig. 4. **a)**, **b)**, **c)** Instantaneous network power consumption if different time periods and **d)**, **e)**, **f)** Changes in trend of average energy savings coefficient

instantaneous network power consumption obtained for ILP model ME/FC and heuristic algorithms H-ME/FC and HM-ME/FC. For each of them, we can notice higher values of instantaneous network power consumption during each time period when compared with power consumption of other ILP models and heuristic algorithms presented in **Fig. 4-(a)** and **4-(c)**. This is because guaranteeing full SA coverage at any moment during a day requires a higher number of network devices to be powered on, which consequently results in higher instantaneous power consumption of WLAN. If we compare results in **Fig. 4-(a)** with those presented in **Fig. 4-(c)**, we can see that the limitation of frequent variations in activity of CSs introduced by H-MELV and HM-MELV heuristics does not introduce a significant increase in instantaneous power consumption. Therefore, the approach tending to preserve powered on CSs in subsequent time periods can be considered for practical implementation. This is important since reduction of frequent re-association of users and minimization of signaling overheads will be of great significance for future energy-efficient management systems.

Moreover, in the case of network power consumption, results obtained for the heuristics closely pursue those of corresponding ILP models. Generally, **Fig. 4-(a)**, **4-(b)** and **4-(c)** show that results of instantaneous power consumption in most time periods are for heuristics up to 10% higher in comparison with results obtained by the corresponding ILP models. This is a consequence of the suboptimal nature of heuristics which offers the best possible solution for a given problem. Also, somewhat higher instantaneous power consumption of heuristics influences on coefficient of average energy savings which is according to **Fig. 4-(d)**, **4-(e)** and **4-(f)** something lower than those of ILP models. In **Fig. 4-(d)**, **4-(e)** and **4-(f)**, we can notice that higher energy savings can be obtained during time periods of lower user activity (t=1, 5) and vice versa. This confirms that usage of developed heuristic algorithms ensures adaptation of network energy consumption to variations in traffic load. When compared with energy consumption of nowadays WLANs that lack any energy efficiency, this result with minimization of monthly network energy consumption (**Fig. 5**).

6.2 Energy consumption and computation complexity

To prove the convenience of the proposed ILP and heuristic optimization framework, we performed five separate tests for each network structure presented in **Fig. 1** and **2**. Network structures have properties as stated in **Table 1**. Each testing differentiates in allocation of TPs, which was random inside the CA of each CS. By performing analyses for each of nine proposed models on five network instances of different SA size, we obtain 150 optimization results in terms of monthly energy consumption. Due to space shortage, in **Fig. 5** we present average values of these results, while in **Fig. 6** we present average value of computational time elapsed before reaching a feasible solution.

Slightly higher values of power consumption presented in previous Section for the case of heuristics are directly reflected in higher monthly energy consumption shown in **Fig. 5**, for each of the considered WLAN instances. In **Fig. 5** it can also be noticed that modified versions of heuristics (HM-ME, HM-ME/FC, HM-MELV) have a little bit higher monthly energy consumption for every instance, when compared with corresponding native heuristics (H-ME, H-ME/FC, H-MELV). It is a result of a simpler neighbor search process during the LS phase, which terminates on the first randomly selected neighbor. This approach reduces the possibility of finding a better neighbor which consequently results with a somewhat higher value of monthly energy consumption. Obviously larger network instances with a higher number of network devices (APs) consume more energy, regardless of the fact that energy-efficient network management has been implemented. Nevertheless, even such energy consumption is according to **Fig. 5** significantly lower if compared with reference energy consumption of WLANs lacking any management schemes.

Although heuristic approaches offer inferior results of monthly energy consumption in comparison with results obtained by corresponding ILP models, for reaching final solution, heuristics need significantly lower computational time. This can be clearly seen in **Fig. 6**, which confirms that the size of some network instances directly influences computational complexity of the optimization problem and consequently on the time needed for finding the final solution. According to **Fig. 6**, computational time for small network instances is very low, having values of the order of less than one minute for both heuristics and mathematical models. Hence, for small network instances, the size of optimization problem is small and computation of final solution becomes fast.

For medium size instances, an enormous increase in computational time of ILP models (ME, ME/FC, MELV) forced us to terminate the optimization process after 24 hours. Actually, for medium size network instances CPLEX solver cannot reach an optimal solution in one day (24 hours). This is because analyzed optimization problems belong to the NP-hard category of problems, lacking any known algorithm that can find an optimal solution in polynomial time. On the other hand, for the same network instance each of the proposed modified heuristics finds a solution to the optimization problem in 100 times shorter period (**Fig. 6**).

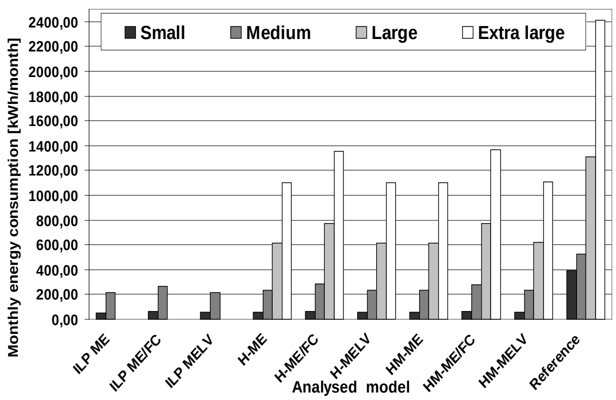


Fig. 5. Monthly energy consumption of ILP models and heuristic algorithms for analyzed instances

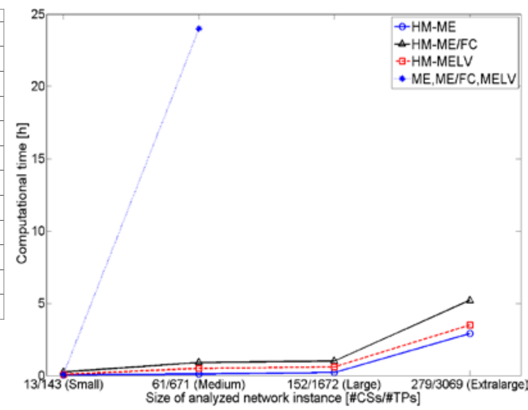


Fig. 6. Dependence of computational time on size of analyzed instances

Moreover, mathematical (ILP) models solutions using CPLEX solver have not been tested against large and extra-large network instances. This is because computational time will be enormous (much longer than 24 hours), lacking any possibility for practical implementation of ILP models. Nevertheless, for networks of large and extra-large size, heuristics (HM-ME, HM-MELV) still offer a final solution in a reasonable amount of time (**Fig. 6**). This time equals up to a few hours (**Fig. 6**) even for extra large instances, which can be acceptable from a practical point of view. It is because the optimization process in such large WLANs can be split into smaller parts, where a few separate optimization processes can be dedicated to predefined parts of the network. For the case of small and medium size network instances, the results presented in **Fig. 5** and **6** have been obtained with allocation distance of MPs equal to 10 m × 10 m. For large and extra-large network instances having area sizes of almost three and five square kilometers respectively, results have been obtained for lower dispersion of MPs equal to 30 m × 30 m. It is reasonable to believe that with this allocation density of MPs in areas of such sizes we still guarantee full SA coverage.

Although heuristics offer a final solution without guaranteeing optimality, in the context of computational time heuristics obviously outperform CPLEX solver. With reasonable computational time and a final solution that is at a maximum 10% worse than the solution obtained by ILP models and CPLEX solver, heuristics can be a valuable alternative to the ILP approach in practical implementations.

7. Conclusion

In this paper, we have considered the problem of optimizing the energy consumption of WLANs through switching on and off and adjusting the emitted power of access stations based on realistic traffic patterns. We have proposed several ILP optimization models and corresponding heuristic algorithms that allow selection of optimal network configuration in terms of energy consumption. While ensuring minimization of network energy consumption, some of the proposed heuristic algorithms can guarantee full SA coverage or limit frequent variations in activity of network devices. Although heuristics offer somewhat inferior results of instantaneous power consumption and monthly energy savings, in terms of computational time, heuristic algorithms clearly outperform corresponding ILP models. Even for the optimization problems analyzed on the largest network instances, heuristics still give a feasible solution in a reasonable amount of computational time. This makes heuristics algorithms convenient for practical implementation in real network management systems. We are currently working to extend proposed ILP models and heuristic algorithms to consider possible energy savings in wide area wireless access networks like 2G/3G/4G networks.

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