Optimized Network Management for Energy Savings of Wireless Access Networks*

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Abstract – The energy consumption of wireless access networks is rapidly increasing and in some countries it amounts for more than 55% of the whole communication sector and for a non negligible part of the operational costs of mobile operators. The new wireless technologies with a growth of data rates by a factor of roughly 10 every 5 years and the increase in the number of users result in a doubling of the power consumption of cellular networks infrastructure every 4-5 years - to 60 TWh in 2007.

In this paper we consider possible energy savings through optimized management of on/off state and transmitted power of access stations according to traffic estimates in different hours of the day or days of the week. We propose an optimization approach based on some ILP models that minimizes energy consumption while ensuring area coverage and enough capacity for guaranteeing quality of service. Proposed models capture system characteristics considering different management constraints that can be considered based on traffic requirements and application scenarios. Energy minimization problems are solved to the optimum or with a gap to the optimum of less than 2.7% on a set of synthetic instances that are randomly generated. Obtained results show that remarkable energy savings, up to more than 50%, can be obtained with the proposed management strategies.

Keywords: **Energy savings, optimization, wireless, management, green networking, power consumption, energy-efficiency.**

1. Introduction

During last decade, energy consumption of information and communication technologies (ICTs) sector has become a key issue, from ecological, energetic and economic point of view [1]. ICT contributes with 2% (0,8 Gt CO2) of global greenhouse gas (GHG) emissions annually [2], [3], thus exceeding GHG emission of aviation sector [4]. As ICTs become more widely available, these percentages are likely to grow in the next years to around 1,4 Gt of CO_2 by 2020, or approximately 2,8% of global emissions at that date [5], [3]. Also, ICT alone is responsible of a percentage which varies between 2% and 10% of the world power consumption [4], [6]. Estimated consumption of the network equipment (excluding serves in data centers) in 2007 was 22 GW, and with predicted annual growth rate of 12% it will reach 95 GW in 2020 [5].

Although mobile radio networks, as one part of the ICT sector, contributes a rather small portion of the global GHG emissions (0,2%) [7], [8] energy consumed by this sector is not negligible. In wireless networks, upgrowth of data rates by a factor of roughly 10 every 5 years ("Moore's Law") results in a doubling of the power consumption of cellular networks infrastructure (base stations and core network) every 4-5 years - to 60 TWh in 2007 [9]. Besides growth in the data rates supported by implementation of new wireless technologies (migration from 2G to 3G or from IEEE 802.11g to 802.11n), most of operators are forced to keep older technologies (for example 2G) in parallel operation with the new ones (3G). In addition, the need for enlargement of network capacity due to increase in the number of new users will additionally raise energy consumption [10]. Also, according to [11] the energy consumption of mobile telephony operators in Italy is equal to 0,7% of total national electric consumption. This is equivalent to 55% of energy consumed by all communications sector. Therefore, with rising demand for wireless communication services, serious challenges with respect to energy needs of mobile radio networks are expected in the future.

Furthermore, economical reasons such as possible minimization of operational expenditures (OPEX) impose cellular network operators and other owners of wireless network devices to consider reducing the energy consumption of their networks. This is contributed with permanent increase in the unit price of consumed electrical energy (kWh) through last decade, with predictions of further growth above 200% in the next 5-10 years [12]. Two important reasons motivate investigations for achieving higher energy efficiency in radio part of the wireless access networks. Firstly, over 80% of the power in mobile telecommunications is consumed in the radio part of the wide-area access network, more specifically the base stations (BSs) [7], [8]. Secondly, the number of enterprise deployments and the average number of access points (APs) in each enterprise wireless local area network (WLAN) increases exponentially every year [13], [6]. For example, only in the year 2009, around 50 million of new APs have been shipped to the world market and for 2010, estimated global APs shipments will exceed 70 million units [14]. Although energy consumption of a BS is much higher in comparison to an AP, vast number of WLAN network devices installed worldwide contribute to the enlargement of energy consumption in wireless access networks.

Mentioned reasons ask for the development of new energy saving approaches on both, micro and macro level of the wireless access networks. Improvements of individual network devices on the micro level are based on the use of more energy efficient and load adaptive hardware components as well as software modules [15], [3]. However, macro approaches, that consider the entire network energy consumption in the network design, planning, and management phases are absolutely important for achieving

* Preliminary results have been presented in [21].

remarkable energy savings. This is especially important for already deployed wireless access networks, since expected network life cycle does not allow frequent replacements of network equipment. Therefore, in this paper we consider potential macro level advances which take into account management strategies of whole wireless network through optimal selection of active network resources. Such energy-efficient resource management strategies must enable wireless access networks to scale energy consumption with the number of active users and its capacity demands.

Wireless access networks are mostly dimensioned for peak demands using dense layers of cell coverage in order to ensure sufficient capacity in areas where large number of users is expected to be simultaneously active. Although mobile users benefit redundant capacity during times of peak demands, it is known that peak demand rarely occurs [16]. Additionally, reduction of the traffic in some areas of wireless network is due to combination of the typical day-night behavior of users and daily movements of users carrying their mobile devices from residential to office areas and back. Therefore, we believe that significant energy savings can be achieved if parts or all components of some wireless network devices are powered off when traffic is low, and powered on based on the volume and location of user demand. To achieve this for large-scale wireless networks without hampering coverage and/or client performance, a centralized network management approach based on traffic estimations of different hours of the day and days of the week seems to be the most appropriate. This can be easily implemented in current wireless access systems since network management architectures of today's wireless access system already provide to network supervisors full control of network elements and tools for measuring traffic statistics with rather fine granularity. Hence, in this work, we propose an optimization approach for managing the network that is based on mathematical programming. Our goal is to develop general energy optimization models that can be applicable for different wireless access technologies (WLAN, WiMax, 2G/3G/4G), even though in this paper we will focus on WLANs.

The rest of the paper is organized as follows: Section 2 gives an overview of the previous research activities in the area of green networking focusing in particular on wireless access networks. Section 3 discusses the influence of changes in transmitted power on consumed power, transmission rates and cell coverage in WLANs. Estimation of the APs capacity load with network structure and traffic pattern used for our analyses are described in detail in Section 4. In Section 5, the mathematical models proposed for optimizing the energy consumption according to assumed traffic pattern are presented. Generator of solver input data with reference models for estimation of energy savings are presented in Section 6. Obtained numerical results are discussed in Section 7, while in Section 8 we give some concluding remarks.

2. Related work

Reducing the power consumption of wired network links and network devices was firstly considered by Gupta and Singh in [1]. Although our paper focus on investigations of energy savings in the wireless access networks, two important works [15], [17] considering integer linear programming (ILP) for optimization of power consumption in wired networks will be mentioned. Authors in [15] propose novel greedy heuristic algorithms for switching off network nodes and links, by solving NP-complete network design problem using ILP formulation. In work [17], mixed ILP techniques are used to investigate power consumption, performance and robustness in static network design and in dynamic routing. These papers indicate that mathematical programming based on the ILP formulation can be used as powerful tool for modeling possible energy savings of real networks.

Furthermore, it is important to emphasize that topic considering energy savings in wireless access networks has attracted the attention of the research community very recently, and some initial ideas and results appear in [4], [6], [7], [13], [18], [19], [20], and [21]. Significant paper [13] makes the first attempt for adoption of resource on-demand (RoD) WLAN strategies that can reduce energy consumption of centrally managed WLANs without adversely impacting the performance of clients in the network. The most important message of this paper is that the energy wasted in large-scale and high-density WLANs is a new and serious concern, which can be reduced through on-demand powering of APs. Analytical model for assessment of the effectiveness of RoD strategy introduced in [13] has been proposed by authors in [18]. The proposed model is used for studying two simple on-demand polices, that, based on instantaneous WLAN parameters, select the appropriate number of APs to activate, thus trying to avoid to waste energy on underutilized APs. Authors show that for the case of both polices, ample room exists for energy savings. In article [19] 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.

According to work presented in [6], it is possible to switch off some UMTS cells and Node B's in urban areas during low-traffic periods, while still guaranteeing quality of service (QoS) constraints in terms of blocking probability and electromagnetic exposure limits. The same authors in [4] derives expressions for the optimal energy saving as a function of the daily traffic pattern, proving that energy savings of the order of 25 - 30% are possible for several regular cell topologies. The impact of deployment strategies on the power consumption of mobile radio networks considering layouts featuring varying numbers of micro base stations per cell in addition to conventional macro sites has been investigated in [7]. Obtained results suggest that, for scenarios with full traffic load, the use of micro base stations has a rather moderate effect on the area power consumption of a cellular network. In [20], the authors evaluate the energy saving that can be achieved with the energy-aware cooperative management of the cellular access networks of two operators offering service over the same area. Authors claim that huge amount of energy can be saved, and suggest that, to reduce energy consumption, new cooperative attitudes of the operators should be encouraged in the future.

Table 1. Average power consumption and coverage-PHY rates dependence for different levels of Tx power

Level of transmitted power k	Baseline pow. cons. P_b (W) - Power profile 1|2	Additional pow. cons. P_k (W) - Power profile 1|2	Average pow. cons. $P(k)$ (W) - Power profile 1|2	Tx power P_k (mW/dBm)	Max. coverage distance (m) for -83 dBm sensitivity	Received signal strength at 120 m (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|10	7|2	12|12	100/20	126,619	-82,3678	R_{j11}=54	R_{j12}=36	R_{j13}=18
2	5|10	5|1,5	10|11,5	75/18,8	114,314	-83,5670	R_{j21}=48	R_{j22}=24	R_{j23}=12
3	5|10	3|1	8|11	50/17	98,034	-85,3678	R_{j31}=36	R_{j32}=18	R_{j33}=9
4	5|10	1|0,5	6|10,5	25/14	75,910	-88,3678	R_{j41}=24	R_{j42}=12	R_{j43}=6 (N/A)
Average PHY rates ($\overline{R}_{jkr}$) for each coverage ring (Mb/s)							$\overline{R}_{jk1}$=40,5	$\overline{R}_{jk2}$=22,75	$\overline{R}_{jk3}$=11,25
Minimal number of UTs (TPs)/coverage ring							6	3	2

Table 2. Path-loss model and simulated network parameters with monthly energy consumption of RMs

Path-loss model values		Simulation network parameters					Reference consumption for PP1 models		
		Area	Area dimensions (m×m)	Area size (m^2)	Number of APs (CSs)	Number of UTs (TPs)	RM#1 (kWh/ month)	RM#2 (kWh/ month)	RM#3 (kWh/ month)
λ =0,122 m	f=2,4 GHz	SA	1.182x844	997.608	61	671	527,04	363,24	416,7
X_σ=6,23 dB	σ=13 dB	CA#1	238x844	200.872	5	55	43,2	37,44	43,2
d_0=1 m	$\overline{P}_{pl}(d_0)=40$dB	CA#2	472x844	398.368	23	253	198,72	139,26	164,16
n = 2,7	$P_{rtr}(d)$=-83 dBm	CA#3	472x844	398.368	33	363	258,12	186,54	209,34

Generally, these articles are based on a strict classification of access devices in those that remain permanently powered on and the others that switch between on/off states according to user activity. This approach reduces flexibility in the selection of optimal number of active devices and usually is not able to achieve optimal energy savings, while it guarantees good levels of QoS. Moreover, all previous work do not provide results on possible energy savings for real size wireless access networks. To the best of our knowledge, our recent positioning paper [21] was the first one that applies ILP principles in order to minimize power consumption of a wireless access network. We have proposed a mathematical model that selects the optimum network configuration in terms of instantaneous power consumption, while ensuring enough capacity and coverage for active users in the service area (SA). Obtained results have been extended in this paper with derivation of ILP models able to optimize energy consumption of wireless access network according to traffic profiles on a set of time periods, while guaranteeing at any time, complete coverage of the SA and enough system capacity.

Finally, it is worth mentioning that energy consumption is a well studied topic in the area of wireless sensor networks where devices are battery operated [22]. However, there are several basic issues that make the problem of managing energy in wireless access network different than in wireless sensor networks. First of all, most of the work on sensor networks is focused on energy efficient routing protocols and medium access control strategies, while with wireless access network we consider mainly the dynamic management of the on/off states of access devices. Moreover, the studies on sensor networks that consider the management of the sleeping time of sensor nodes mainly try to partition the set of nodes in groups activated in different periods in order to maximize the network lifetime [23]. This is different from the case of wireless access networks since we are not interested into the individual energy consumption and access devices that are more important for the coverage can stay powered on longer than the other. This results in a quite different structure of the model also from a mathematical point of view.

3. Power consumption model

3.1 AP power consumption

In order to define input parameters for mathematical models presented later on, we consider as an example the energy consumption of IEEE 802.11g WLAN networks, with APs and user devices working in infrastructure mode. We start from the assumption that average electric power consumed by wireless network devices depends also on the transmitted (Tx) power of radio signal [7]. Two components, fixed and variable contributes to the average power consumption of the wireless network devices. Fixed component (AC/DC conversion, signal processing, filtering, cooling, etc.) does not depend on the radiated power and is constant in time. Hence, even if the radio interface does not transmit, the device still consumes electric power. This baseline power consumption is denoted as P_b (W). On the other hand, variable component of the power consumption P_k (W) due to power amplifier, feeder losses and cooling depends on the radiated power P_{Tk} (mW, W or dBm) and is higher when radiated power increases. Accordingly, power consumption of the network devices can be expressed as function of the Tx power. If wireless network device transmits radio signal with the Tx power P_{Tk}, baseline power consumption P_b increases for amount of P_k resulting in instantaneous (average) power consumption equal to

$$P(k) = P_b + P_k \qquad \text{[W]} \qquad (1)$$

where $k \in K = \{1,...,l\}$ is one of l possible levels (values) of the Tx signal power P_{Tk}. Similar considerations can be done for network devices of some other wireless technologies, including 2G, 3G, 4G and WiMax systems.

Correlation between level k of the Tx power P_{Tk} and additional electric power P_k consumed by WLAN AP can be assumed as shown in Table 1. Generally speaking, *maximal declared power consumption* of the APs working in compliance to IEEE 802.11b/a/g standards varies between 5 W and 13 W. These values greatly depend on the number of different 802.11 radios, simultaneously supported by a single AP device. Since new generations of APs based on 802.11n standard have multiple antennas exploiting benefits of multiple input-multiple output technology, higher number of transceiver circuits dedicated to each antenna imposes power consumptions that in most cases exceeds 13 W, and can go above 20 W. Furthermore, declared power consumption can differ among APs of different manufacturers, even if they support the same 802.11 technologies. This is shown in the study [24], where significant differences in energy efficiency expressed in Joules per Megabit (J/Mb) of transferred traffic have been reported for APs of various manufacturers. In addition, differences in energy efficiencies are due to different configuration parameters of APs (Tx power, security-encryption, etc.). Typically, the radio front end of the wireless APs is designed using a Class A power amplifier (PA) in order to increase the signal strength radiated by the antenna. Although the Class A amplifier requires the AP to have a fairly constant power draw, for the sake of integration to the proposed mathematical models, it is assumed that increase in a Tx power level results in growth of consumed electric power due to larger PA consumption and antenna losses. This is undoubtedly truth, although it is sometimes hard to detect in practical measurements of instantaneous AP power consumption. As presented in the Table 1, two power profiles (PPs) with different values of the P_b and P_k, have been considered. Also, it is worth to note that previous Power over Ethernet (PoE) IEEE 802.3af [25] standard can not satisfy power demand of the new generation of network devices since it prescribes up to 12,95 W of DC power. Due to advent of more power hungry devices as IEEE 802.11n APs, IEEE recently ratified new Power over Ethernet (PoE) standard known as IEEE 802.3at [26], providing up to 25 W of DC power to remotely powered devices.

3.2 Transmitted power and coverage range

Changes in the Tx power also influence on channel condition estimates used for adaptive selection of the best rate out of multiple available Physical Layer (PHY) rates defined by IEEE 802.11g standard [27]. Because of that, for different Tx power levels P_{Tk} of wireless device (AP), users allocated at the distance d from AP have different PHY transmission rates as indicated in Table 1. We assume a set D of different number of coverage rings $r \in D = \{1,...,e\}$ which corresponds to different coverage areas of every AP as shown on Figure 2a). We considered a number $e=3$ of coverage rings with borders $0 \le d \le 40$ m for $r=1$, 40 m $< d \le 80$ m for $r=2$, and 80 m $< d \le 120$ m for $r=3$. All users located in the *r-th* coverage ring will have the same PHY rate, which can be treated as average transmission rate of corresponding coverage area. Maximal coverage range of 120 m is typical for moderately obstructed indoor WLAN environments. In real scenarios coverage areas are not circular as channel attenuation does not depend on distance only, but it is also influenced by other effects like obstacle shadowing.

The log-distance path loss model considering log-normal fading expressed as

$$P_{pl}(d) = \overline{P_{pl}}(d_0) + 10n\log_{10}\left(\frac{d}{d_0}\right) + X_\sigma \qquad \text{[dB]} \qquad (2)$$

is the propagation model used in our analyses for characterization of WLAN radio environment [28], [29]. In relation (2), $\overline{P_{pl}}(d_0)$ is average value of the path loss at close-in reference distance d_0, n is path loss exponent and X_σ is zero-mean Gaussian distributed random variable having standard deviation σ. Values used for calculation of the received power given by

$$P_r(d) = P_{Tk} - P_{pl}(d) \qquad \text{[dBm]} \qquad (3)$$

at Euclidean distance d between transmitter and receiver are shown in Table 2. Furthermore, increase of Tx power results in enlargement of coverage area size and vice versa. For simplicity however, we assume no changes of coverage radii with transmit power scaling, but we account this effect through scaling of the PHY transmission rates. For each of Tx power levels, values of the PHY rates presented in Table 1. are selected according to the results in [30], [31]. Furthermore, [32] suggests that 3-5 discrete Tx power level choices are sufficient to implement any robust power control mechanism in typical indoor WLAN environments. This is the reason why we have considered a set K with four ($k=1, 2, 3, 4$) Tx power levels. The highest level is 100 mW, since this value is the maximum power indicated by spectrum usage rules in most countries.

Although IEEE 802.11 PHY mandates scaling of sensitivity values based on the used PHY rate [27], as further simplification, constant receiver sensitivity (P_{rth}) of -83 dBm has been considered for all PHY rates. Selected sensitivity value is characteristic for most of the new WLAN cards [33], [34]. According to the calculated received signal strengths at 120 m from AP and based on maximal coverage distances for sensitivity of -83 dBm (Table 1), assumptions about potential connections between user and network devices (APs) can be made. Actually, connection between user terminal and AP can be obtained in the third ($r=3$) coverage ring if the level of received signal strength is below *power sensitivity threshold*: $P_r(d) \le P_{rth}$. This is the reason why for the lowest Tx power level ($k=4$, P_{Tk}=25 mW) in the third coverage ring ($r=3$), connection can not be establish (N/A in Table 1).

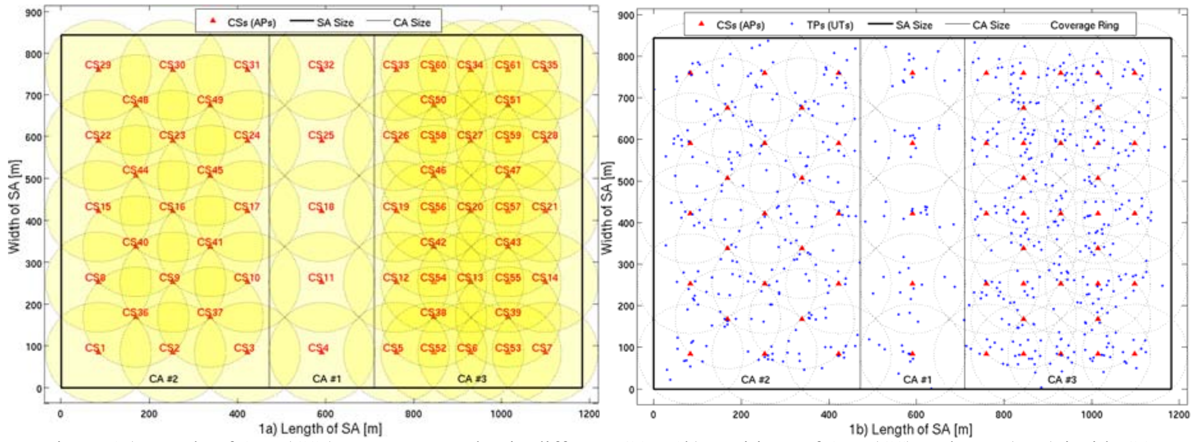


Figure 1a) Levels of APs (CSs) coverage overlap in different CAs, 1b) Positions of APs (CS) and UTs (TPs) inside SA

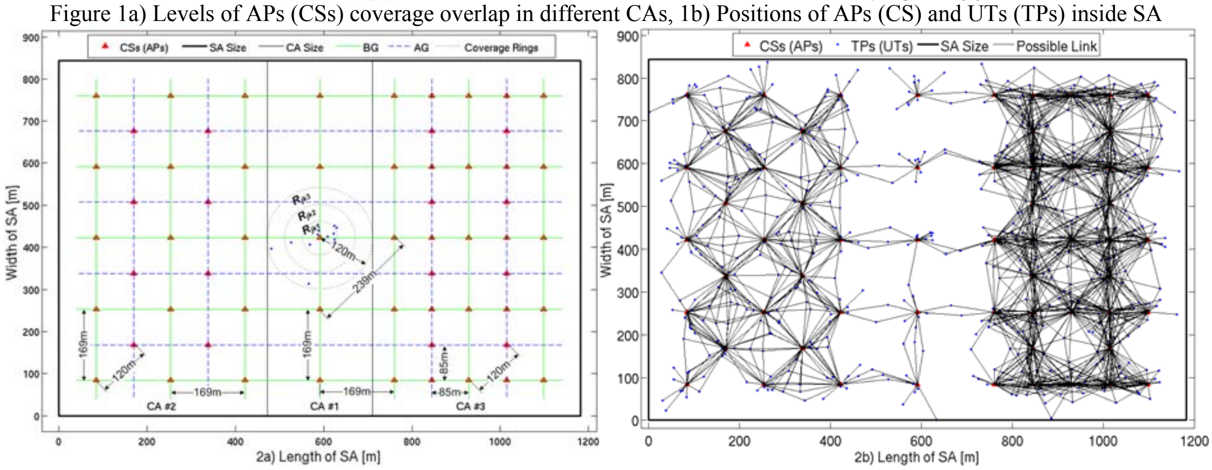


Figure 2a) Coverage rings of CSs (APs) allocated in the grid manner, 2b) Possible wireless connections between CSs and TPs

4. Network and traffic model

4.1 Structure of the service area

The energy management strategy that we propose applies to wireless access networks in operation. These networks are the result of a design phase that usually considers the characteristics of the area to be covered and expected traffic distribution. Hence, for testing the proposed energy management strategy, we tried to emulate the topology of a realistic WLAN. In order to satisfy APs capacity constraints, it is assumed that higher densities of APs need to be present in the areas where higher concentration of user terminals (UTs) are expected (Figure 1b). Additionally, for satisfying coverage constraint, every part of the SA is assumed to have basic wireless coverage (Figure 1a).

Based on the concentration of APs in some parts of the SA, three different coverage areas (CAs) presented on Figure 1a) have been considered. Types of CAs will differ in the level of the cell overlap and can be categorized as:

- First coverage area (CA#1) providing *low overlapping* with almost no redundant layers of cell overlap. This covering approach can be applicable to in-building halls or storages where simultaneous activity of large number of users is not expected.
- Second coverage area (CA#2) having *moderate overlapping* with the average number of 2-3 layers of wireless signal. Such network planning approach can be suitable for coverage of office areas with sober user concentrations.
- Third coverage area (CA#3) is characterized with *high overlapping,* offering 3-4 layers of wireless signal. This dense coverage can be most convenient for conference or waiting rooms where huge number of users will simultaneously request network resources.

Location of the APs inside SA is performed according to a grid structure (Figure 2a). By selecting different horizontal, vertical and diagonal distances (Figure 2a) of the AP locations we create three CAs with distinct levels of cell overlapping. A minimal number of 11 user terminals (UTs) located inside coverage area of each AP (Figures 2a and 1b) have been selected. In addition, exact number of UTs placed in the first, second and third coverage ring are 6, 3, and 2, respectively (Table 1). Note that all 11 UTs located inside coverage area of one AP can potentially be in the coverage area of some other AP(s) (Figure 1b) and selection of UT positions inside coverage rings of each AP is completely random.

Table 3. Number of active users, duration and average demand values of each CDV

				Approximation with three time periods			Approximation with five time periods			Approximation with seven time periods		
Time period/ CDV number t	CDV indexing ($\mathbf{d}_{it}$)	Range of user demands in CDVs (Mb/s)	Average demand of CDVs (Mb/s)	T_t (h)	T_{t+1} (h)	% of active users in CDVs	T_t (h)	T_{t+1} (h)	% of active users in CDVs	T_t (h)	T_{t+1} (h)	% of active users in CDVs
1	$\mathbf{d}_{i1}$	1,8-2,2	2	00	09	25	00	09	20	00	06	15
2	$\mathbf{d}_{i2}$	1,8-2,2	2	09	18	100	09	12	100	06	09	60
3	$\mathbf{d}_{i3}$	1,8-2,2	2	18	24	60	12	15	70	09	12	100
4	$\mathbf{d}_{i4}$	1,8-2,2	2	N/A	N/A	N/A	15	18	85	12	15	70
5	$\mathbf{d}_{i5}$	1,8-2,2	2	N/A	N/A	N/A	18	24	55	15	18	85
6	$\mathbf{d}_{i6}$	1,8-2,2	2	N/A	N/A	N/A	N/A	N/A	N/A	18	21	45
7	$\mathbf{d}_{i7}$	1,8-2,2	2	N/A	N/A	N/A	N/A	N/A	N/A	21	24	30

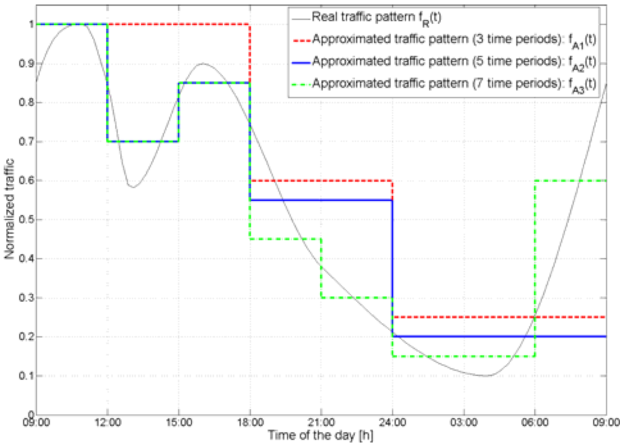


Figure 3. Real and approximated traffic pattern of analyzed WLAN

Hence, indoor, moderately obstructed SA (1.182 m x 844 m) of almost 1 million square meters (Table 2, Figures 1a and 1b) is used for analyses with precise dimensions of each CA presented in the Table 2. Such SA structure can correspond to a travel terminal like airport or train station building(s). Figure 1b) illustrates the final architecture of the analyzed network consisted of 61 APs and 671 UTs. All potential wireless connections between every UT and one or more AP(s) are presented on Figure 2b).

4.2 Capacity load estimation

During a network planning phase, it is necessary to estimate user locations and their demand of network resources. Since in our case the goal is to evaluate an energy management approach that switches on and off network devices according to the traffic pattern, we need to make some assumptions on how the network is dimensioned according to AP capacity. Since in the most cases capacity planning of wireless networks is based on user traffic during peak time periods, in order to estimate the peak load of a single AP in the network, we make the following assumptions:

- during peak time periods an average number of 11 UTs allocated in corresponding coverage rings share capacity of a single AP,
- for each user, average PHY rate (bandwidth) equal to approximately 2 Mb/s must be ensured at any time.

Due to the CSMA/CA mechanism, guaranteed bandwidth of the 2 Mb/s corresponds to approximately 800 kb/s of the effective throughput. If shared AP capacity is normalized to 1, overall user demand (d_i) on AP capacity resources can be expressed as

$$\sum_{r\in R}\sum_{i\in I(jkrt)}\frac{d_i}{\overline{R}_{jkr}}=\frac{6\times 2Mb/s}{40{,}5Mb/s}+\frac{3\times 2Mb/s}{22{,}75Mb/s}+\frac{2\times 2Mb/s}{11{,}25Mb/s}=0{,}90\leq 1 \qquad (4)$$

where the $\overline{R}_{jkr}$ defines a*verage PHY rates of the three coverage rings* as shown in the Table 1 and a maximum load of 90% is assumed considering 6, 3 and 2 UTs in the three coverage rings. Average PHY rates are considered since equal usage probability of all Tx power levels in each coverage ring can be assumed. When powering off some APs, associated users must be reconnected to the other APs that remain powered on and this result in enlargement of their capacity load. In the case of traffic patterns having less than 100% of active users, redundant capacity of 10% is enough to take over capacity demands of additional users connected to the APs which remain powered on. Otherwise, for traffic pattern with all UTs active, estimated redundant capacity of 10% must be enlarged in order to accommodate more than 11 users per AP. This can be done using transmissions with the highest Tx power levels (*k=1,2*). In this case, higher PHY rates (R_{jkr}) compared to the average PHY rates ($\overline{R}_{jkr}$) results in higher capacities offered to the users in each coverage ring (Table 1). Therefore, considered network has enough redundant capacity for powering off some APs, even in scenarios with maximal number of active UTs.

4.3 Traffic pattern for different time periods

In this paper we consider realistic traffic pattern, modeled based on measurements presented for different types of wireless access networks [35], [13], [16]. The continuous function $f_R(t)$ on Figure 3. depicts assumed daily traffic pattern, normalized to the peak, so that $f_{R\max}(t)=1$ occurs at the peak hour (11 a.m.). Although assumed traffic pattern may differ from those of some other wireless access networks, still, this pattern can be considered as a good representative of real user activity in WLANs. To generate numerical results, discrete function $f_A(t)$ presented on Figure 3. is used for approximating the normalized daily traffic pattern $f_R(t)$. It is possible to define ordered set H of all daily time periods as $t \in H = \{1,...,p\}$, with p representing maximal number of different time periods in a day. Time periods p are expressed in hours (h) as time difference between ending (T_{t+1}) and starting time (T_t) of period t. The end of the previous time period is the beginning of the new time period and there is no time gap between adjacent time periods (Figure 3). Total duration of all time periods must be obviously equal to the number of hours in a day (24 h). Table 3 presents traffic profiles using $p=3$, 5, and 7 different time periods.

During each time period t, traffic generated by user terminals can be expressed in the form of a *capacity demand vector* (CDV)

$$d_{it}=\left[d_{1t},...,d_{it},...d_{nt}\right]^T \qquad (5)$$

where d_{it} stands for capacity demand (Mb/s) of *i-th* user terminal. Active users in period t are those with nonzero value of d_{it}. As presented in Table 3, for each time period t, the number of active users corresponds to the percentage of active users defined by the traffic pattern $f_A(t)$ (Figure 3). Furthermore, in order to provide enough bandwidth to every active user, random distribution of capacity demands in the range between 1,8 Mb/s and 2,2 Mb/s are generated for each active user in the CDV. For simplicity, we consider traffic patterns to be the same for all days in the week (or month). Hence, we neglect traffic differences between working and weekend days.

4.4. Modeling traffic distribution

A simple and commonly adopted way to model the radio coverage in the SA is to consider possible positions of user terminals called test points (TPs) [36]. TPs are defined as discrete points in the SA that are centroids of traffic to be covered by the activated APs. Each TP is characterized by the amount of traffic generated usually measured in bit/s or Erlang. This discrete modeling of traffic is particularly important to define a finite set of points where the optimization model can check for the coverage of the system and the capacity limits of APs activated. The discrete modeling approach to traffic in wireless networks has been originally proposed in [36] and then adopted by basically all literature on radio coverage and by most of radio planning software commonly used by mobile operators [37]. In some cases TPs can be adopted just to allow the optimization model to check for the coverage of the system without defining any traffic offered and thus not consuming capacity of the network. In this paper we call these points Measurement Points (MPs) to distinguish them from TPs and adopt them to define full coverage constraints of the SA. Also, in this case using discrete points is particularly useful to deal with a finite set of coverage constraints.

Obviously, TPs and MPs define static traffic distributions that are the fundamental input to any network dimensioning tool. But, in some scenarios user mobility is an important issue that cannot be neglected. However, since the network cannot be dynamically reconfigured according to user mobility, we are forced to use this discrete model also in the presence of mobility. In this case, however, we assume that traffic description through TPs and MPs considers the worst case (for example the peak traffic in each region) in the considered time period. This ensures that the model can dimension the system considering possible variations due to mobility staying always on the safe side. As for the modeling of available APs in the network, since we are managing the energy of a network already deployed, we just define a set of coverage sites (CSs) that describe the positions of APs that are installed and can be switched on and off in different time periods.

5. Energy consumption minimization

5.1 Formulation of optimization models

The problem of managing energy consumption of a wireless access network is similar to that of network design where however we reduce the capacity of the network by switching off or adjusting the Tx power of some devices according to the traffic pattern. Let:

Table 4. Notation of sets, subsets and indexes

Set (subset) description	Set index	Set Structure	Maximal number of set elements
Set of all coverage sites (CSs): J	j	$j \in J=\{1, ..., m\}$	M
Set of all test points (TPs): I	i	$i \in I=\{1, ..., n\}$	N
Set of all Tx power levels: K	k	$k \in K=\{1,...,l\}$	L
Set of all coverage rings: D	r	$r \in D=\{1,...,e\}$	E
Set of all time periods: H	t	$t \in H=\{1, ..., p\}$	P
Set of all measurement points (MPs): S	s	$s \in S=\{1, ..., u\}$	U
Subsets of Tx power levels detected for (i,j) combination: $K(ij)$	k	$k \in K=\{1,...,l_{i,j}\}$	$l_{i,j}$
Subset of coverage sites (CSs) allocated on intersections of basic grid (BG): J^*	j	$j \in J^*=\{1, ..., m_{BG}\}$	m_{BG}
Sets of CS-configuration pairs covering TP i at time period t: $JK(i,t)$	j_b,k_b	$j_b,k_b \in JK(i,t)=\{(j_1,k_1), ..., (j_{B(i)},k_{B(i)})\}$	$j_{B(i)}$, $k_{B(i)}$
Indexing of $JK(i,t)$ set members (pairs): $b(i,t)$	h	h or $b \in b(i,t)=\{1,..., B(i,t)\}$	$B(i,t)$
Subsets of TPs covered with (j,k) combination in time period t: $I(jkt)$	i	$i \in I(jkt)= \{1, ..., n_{j,k,t}\}$	$n_{j,k,t}$
Subsets of TPs covered with (j,k,r) combination in time period t: $I(jkrt)$	i	$i \in I(jkrt)= \{1, ..., n_{j,k,r,t}\}$	$n_{j,k,r,t}$

- $j \in J=\{1, ..., m\}$ be the set of CSs hosting APs, and
- $i \in I=\{1, ..., n\}$ denote the set of TPs where users (UTs) are placed.

According to relation (1), during each time period t, the *j-th* CS consumes power P_{jb} when it is powered on and additional power P_{jk} when transmitting at *k-th* power level P_{Tk}. For the sake of simplicity we assume all CSs have the same power consumption and Tx power levels with $P_{jb}=P_b$ and $P_{jk}=P_k$. However, these values can be easily adopted if SA comprises APs of different manufacturers having different power consumptions. Figures 1a) and b) presents plots of an example network with TPs and CSs positions. Straight lines between the TPs and CSs on Figure 2b) defines which TPs can be potentially connected to corresponding CS(s), if distance and signal sensitivity restrictions are satisfied for at least one of the Tx power levels.

The problem is to find a set of CSs with minimal power consumption satisfying capacity demand d_{it} (in Mb/s) of all TPs active in CDV during specific time period t. Such problem is a combination of *minimum set covering problem and capacitated facility location problem* and can be formulated using three different binary decision variables: y_{jt}, x_{jkt} and w_{ijkt}. First fundamental decision variables y_{jt} are, as in any covering problem, those selecting which subsets of CSs (APs) are part of the solution:

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

Transmissions of CS j using *k-th* transmit power level (P_{Tk}) will be defined with the second decision binary variable x_{jkt} equal to:

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

Also, binary decision variables w_{ijkt} explicitly indicating assignment of TPs to the CSs are defined as

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

Based on verification of the distance and receiver sensitivity criteria, *0-1 incidence matrix* containing coverage information will be derived for each triple TP i, CS j and *k-th* Tx power level P_{Tk} in the form of binary parameter as

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

Besides already defined sets of Tx power levels $k \in K = \{1,...,l = 4\}$, coverage rings $r \in D = \{1,...,e = 3\}$ and time periods $t \in H = \{1,..., p = 5\}$, two additional sets must be defined as:

- $i \in I(jkt) \subseteq I$ which is the subset of TP(s) in coverage area of CS j transmitting at *k-th* Tx power level during time period t and
- $i \in I(jkrt) \subseteq I$ as the subset of TP(s) allocated in the *r-th* coverage ring for every (j,k) transmit combination during time period t.

Notation of all symbols used for expressing sets and subsets, its indexing and maximal number of elements have been listed in Table 4.

5.2 Basic energy optimization model

Since kilowatt-hour (kWh) is the billing unit used by utility companies for charging consumed electrical energy, this unit has been used for expressing monthly energy consumption of wireless access network. In model development, we start from the assumption that reductions in the daily energy consumption contribute to minimization of the monthly energy consumption. Therefore, objective function is focused on minimization of the network energy consumption caused by CDVs altered during distinct time periods of a one entire day (24 hours). By neglecting somewhat different traffic patterns between working and weekend days, daily network energy consumption obtained as a result of optimization is assumed to be equal for every day during one month. Multiplication of daily energy consumption with the number of days in one month results in total monthly energy consumption that needs to be paid by owners of network equipment.

In order to optimize monthly energy consumption of the wireless access network, we propose the following ILP model named as *Model Energy* (ME):

$$\text{Min}\ \left[\sum_t \sum_j P_j y_{jt}(T_{t+1}-T_t)\right]\times C+\left[\sum_t \sum_j \sum_k P_k x_{jkt}(T_{t+1}-T_t)\right]\times C \tag{6}$$

S. t.

$$\sum_k x_{jkt} \le y_{jt} \qquad \forall(j,t): j\in J=\{1,...,m\}, \forall t\in H=\{1,...,p\} \tag{7}$$

$$\sum_j \sum_k a_{ijkt} x_{jkt} \ge 1 \qquad \forall(i,t): i\in\{1,...,n\}, \forall t\in H=\{1,...,p\} \quad \wedge \quad \forall d_{it}\ne 0: a_{ijkt}\ne 0 \tag{8}$$

$$\sum_{r\in D} \sum_{i\in I(jkrt)} \frac{d_{it} w_{ijkt}}{R_{jkr}} \le 1 \qquad \forall(j,k,t): j\in\{1,...,m\}, k\in\{1,...,l\}, \forall t\in\{1,...,p\} \tag{9}$$

$$x_{j_b k_b t} + \sum_{h=b+1}^{B} w_{ij_h k_h t} \le 1 \qquad \forall(i,t): i\in\{1,...,n\}, t\in\{1,...,p\}, d_{it}\ne 0, \quad s.t.\forall b:\ 1\le b\le B-1 \tag{10}$$

$$w_{ij_h k_h t} \le x_{j_b k_b t} \qquad \forall(i,t): i\in\{1,...,n\}, t\in\{1,...,p\}, d_{it}\ne 0, \quad s.t.\forall b:\ 1\le b\le B, \quad h=b \tag{11}$$

$$\sum_{h=1}^{B} w_{ij_h k_h t} = 1 \qquad \forall(i,t): i\in\{1,...,n\}, t\in\{1,...,p\}, d_{it}\ne 0, \qquad h=b \tag{12}$$

$$\sum_{i\in I(jkt)} w_{ijkt} \le N \qquad \forall(j,k,t): j\in\{1,...,m\}, \forall k\in\{1,...,l\}, \forall t\in\{1,...,p\}, d_{it}\ne 0 \tag{13}$$

$$y_{jt}\in\{0,1\} \qquad \forall j\in\{1,...,m\}, \forall t\in\{1,...,p\} \tag{14}$$

$$x_{jkt}\in\{0,1\} \qquad \forall j\in\{1,...,m\}, \forall k\in\{1,...,l\}, \forall t\in\{1,...,p\} \tag{15}$$

$$w_{ijkt}\in\{0,1\} \qquad \forall i\in\{1,...,n\}, \forall j\in\{1,...,m\}, \forall k\in\{1,...,l\}, \forall t\in\{1,...,p\} \tag{16}$$

$$C=\frac{1}{1000}\times 30 = 0{,}03[1/\text{month}]. \tag{17}$$

In the derived model, summation of parts of the *objective function* (6) in brackets refers to a total energy consumption of wireless network during one day. This consumption can be seen as average daily energy consumption expressed in units of Wh. In order to define objective function of the ME in units of kWh/month, dimensionless multiplication factor corresponding to the *constant C* has been introduced. Value of the constant is defined in relation (17) and is equal to C=0,03 (1/month). This value is used to transform daily network energy consumption expressed in Wh/day in the monthly energy consumption expressed in kWh/month.

Constraints (7) are *coherence constraints* stating that in each CS at most one Tx power level can be used. *Coverage constraints* (8) ensure that all TPs are within SA of at least one CS and *connection constraints* (12) states that every TP i must be connected to only one CS. Since total capacity of each powered on CS is shared between connected TP(s), *capacity constraints* (9) prevents that overall TP demand(s) in the *r-th* coverage ring exceed PHY rate R_{jkr} of that ring. *Best-power selection constraints* (10) make implicit assignment of TPs to the best active CS in terms of the signal strength. In order to satisfy best-power connection criteria, the pairs of CSs and corresponding (Tx) configurations which allows connection with *i-th* TP are sorted in decreasing order of the signal strength, creating for each TP i and time period t set of pairs:

$JK(i,t)=\{(j_1, k_1),...,(j_b, k_b),...,(j_{B(i)},k_{B(i)})\}$.

Index $B(i)$ represents maximal number of a CS-configuration pairs for each set $JK(i,t)$. This index is defined on set $b=\{1,...,B(i)\}$ of ordered (whole) numbers. *Configuration constraints* (11) mandates that a TP i can be assigned to a CS j only if that CS is active and configured with *k-th* transmit power level. In order to eliminate huge number of TPs connected to active CS, *excessive number constraints* (13) limit the overall number (N) of TPs than can be simultaneously connected to the CS. Finally, constraints (14), (15) and (16) are the *integrality constraints* for decision variables y_{jt}, x_{jkt} and w_{ijkt}, respectively. All described constraints must be satisfied

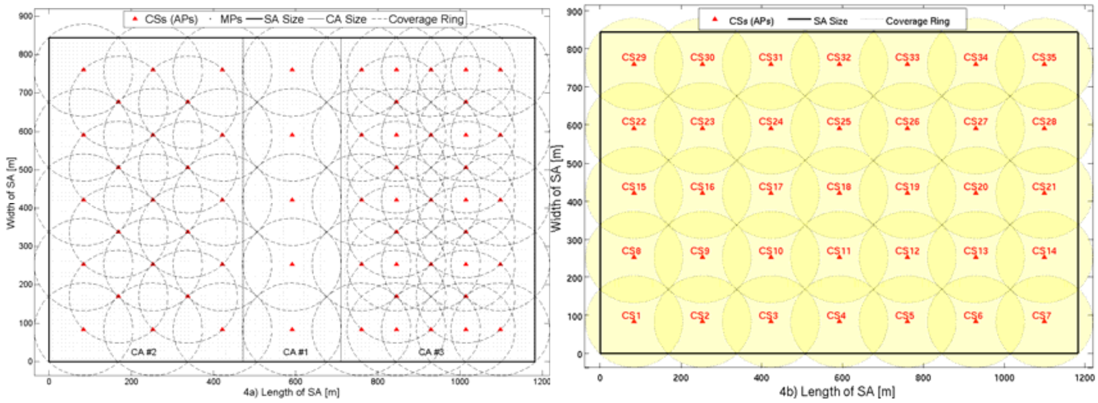


Figure 4a) Dense allocation of MPs inside SA, 4b) CSs that are members of BG subset with corresponding coverage areas

for each time period t. It's easy to see that the optimization problem described by ME is NP-hard since it includes the Capacitated Facility Location Problem, known to be NP-hard, as a special case [38].

Major drawbacks of the presented ME can be found in absence of guarantees ensuring complete coverage of the analyzed SA with wireless signal. On the other hand, it is well known that providing basic coverage of the SA with wireless signal must be one of the major goals when planning and deploying wireless access network. In practice, it is not acceptable to leave some parts of the SA uncovered with a wireless signal by simply powering off some wireless devices in order to accomplish minimization of energy consumption. Although complete SA coverage assurance and minimization of the network energy consumption constitutes two opposite goals, both of them must be satisfied in a future wireless networks. For accomplishment of these goals, some extensions to the presented mathematical model ME must be introduced. In order to develop these extensions, two different approaches guaranteeing full SA coverage will be implemented:

1. an approach to introduce probe points in which satisfactory level of wireless signal must be detected,
2. an approach to introduce set of always powered on CSs.

5.3 Modeling complete coverage

Introduction of virtual points allocated in the grid manner is one way for including in mathematical model constraint that provides at any time, full SA coverage with wireless signal. These virtual points serves as a sort of probe points in which received signal strength must be above minimal sensitivity threshold. As already mentioned in Section 4.4, such points are called measurement points (MP). Figure 4a) presents regular grid of densely allocated MPs inside SA, which are used in this model. It is reasonable to assume that allocation density of MPs with vertical and horizontal distances equal to 10 m (10 m x 10 m) represents fair approximation of all possible user positions inside SA. Thus, by guaranteeing minimal level of wireless signal strength at every MP position, it can be said with great certainty that all SA is covered with wireless signal.

To mathematically model complete coverage of the SA, it is necessary to introduce set $s \in S = \{1,\ldots,u\}$ of the MPs, where u=9.912 corresponds to total (maximal) number of the MPs in the set S (SA). Furthermore, for every MP s belonging to the set S, binary parameter b_{sjk} has been generated according to next premise

$$b_{sjk} = \begin{cases} 1 & \textit{if} \quad s-th \quad MP \quad is \quad covered \quad by \quad j-th \quad CS \quad transmiting \quad with \quad k-th \quad power \quad level \\ 0 & otherwise \end{cases}$$

Calculation of the signal strength at positions of each MP is based on path loss model explained in Section 3.2. If calculated signal strength received from *(j,k) pair* do not exceed sensitivity threshold (-83 dBm), radio coverage of the *s-th* MP will be assumed. Based on this principle, for each MP, *0-1 incidence matrix* containing coverage information can be created. By adding *full coverage constraints*

$$\sum_{j} \sum_{k} b_{sjk} x_{jkt} \geq 1 \qquad \forall (s,t) : s \in S = \{1,\ldots, u\}, \forall t \in H = \{1,\ldots, p\} \tag{18}$$

to the previously derived mathematical model (ME), new model named *Model Energy/Full Coverage* (ME/FC) is derived. According to these constraints, all MPs during every time period t in a day must be covered with radio signal received form at least one *(j,k)* pair.

Another approach for ensuring complete coverage of the SA in a cellular network is inspired by previous research activities presented in the papers [4], [6], [7]. Generally speaking, recent researches in the area of energy savings in wireless access networks are based on classification of wireless network devices in the two categories. The first one constitutes group of a permanently powered devices which remains powered on despite variations in a user activity. In the most cases, those wireless network devices aims to ensure basic level of the SA coverage. The second category is comprised with devices which adopts its on/off state according to a traffic pattern. Such approach is also used in one of the most prominent studies [13] of energy savings in the WLANs, where the proposed algorithm finds permanently powered APs in a finite number of steps.

In order to evaluate energy savings in the networks deployed following described approach, subset J^* of a permanently powered CSs (APs) must be introduced in mathematical model. The J^* is subset of the set of all CSs in the SA ($J^* \subseteq J$) and selection of the subset members can be performed using some algorithm as in paper [13]. Otherwise, members of the subset J^* can be predefined according to assumption based on finding minimal number of APs that must be permanently powered in order to ensure basic radio coverage of the SA. To do this, we exploit grid structure of CS positions (Figure 2b) explained in Section 4.1. According to Figure 4b), 35 CSs allocated at grid points with vertical/horizontal distances equal to 169 m ensure basic coverage of the SA. Hence, this grid is called *basic grid* (BG) and CSs allocated at points of this gird are selected to be members of the subset J^*. Every (CS) member of subset J^* must transmit using maximal Tx power level *(k=1),* since lower Tx powers can not guarantee maximal coverage of 120 m (Table 1).

In order to mathematically express subset J^* of permanently powered CSs, new binary parameter needs to be introduced as

$$c_j = \begin{cases} 1 & if \quad j-th \quad CS \quad is \quad member \quad of \quad subset \quad J^* \\ 0 & otherwise \end{cases}$$

According to this binary parameter, *0-1 incidence vector* containing information about CSs that are members of the subset $J^*=\{1, ..., m_{BG}\}$ can be created. The value of m_{BG} corresponds to the total number of permanently powered CSs inside SA. Using this incidence vector, extension of the ME with *guaranteed coverage constraint* defined as

$$\sum_j c_j x_{jkt} = m_{BG} \qquad \forall (t) : \forall t \in H = \{1,..., p\} \wedge k = 1, m_{BG} = 35 \tag{19}$$

results in creation of new model named *Model Energy/Guaranteed Coverage* (ME/GC). This constraints force every BG CS to transmit with maximal Tx power ($k=1$) during all time periods in a day. According to this model, optimization of energy consumption will be performed for 26 CSs that are not members of the set J^*. For those CSs, adaptive management of on/off state and Tx powers will be performed according to changes in the traffic pattern.

5.4 Limiting configuration variations

Next optimization models are extension of the proposed models: ME, ME/FC and ME/GC. They consider the negative impact that large variations in network configuration from one time period to the next one may have on signaling overhead and perceived service quality. One approach in reducing this impact can be through introduction of *energy penalty* for powering on new CS that was turned off in previous time period. In order to mathematically model such penalty, energy consumed by network device (CS) during booting will be exploited. It is well known that during process of booting all network (electric) devices draws highest power, generally much higher then power consumed during usual operation. Since process of booting lasts very shortly, contribution of energy consumed during booting process to the overall energy consumption of a device is negligible. Nevertheless, values of energy consumed during booting process can be very suitable for modeling energy penalty. Therefore, next assumptions have been taken into account in order to calculate value of energy penalty:

- duration of CSs booting process lasts 30 s and
- average power consumed during this period is fixed and equal to the maximal possible value (12 W).

According to these assumptions, energy penalty for one-time powering of one CS (AP) corresponds to 0,0001 kWh of consumed energy. If CS needs to be powered at the start of emerging time period, assumption is that such powering will happen for every day in the month. This is the reason why energy penalty for powering on single CS between two time periods must be multiplied with the number of days in a month in order to obtain monthly value of the energy penalty defined as

$$E = \frac{30\,s \times 12\,W}{1000 \times 3600\,s} \times 30\,(days) = 0{,}003\,[\text{kWh/month}] \tag{20}$$

To mathematically express influence of this penalty, new binary variable defined as

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

need to be derived. With this binary variable, new objective function considering penalty for powering on CS(s) in subsequent time period can be formulated as

$$\text{Min}\left[\sum_{t=1}^{T}\sum_j P_j y_{jt}(T_{t+1}-T_t) + \sum_{t=1}^{T}\sum_j\sum_k P_k x_{jkt}(T_{t+1}-T_t)\right]\times C + \sum_{t=1}^{T-1}\sum_j z_{jt+1}E \tag{21}$$

By substituting this objective function with the one presented in previous models (ME, ME/FC, ME/GC) and by adding to the previous constraints (9-18) the new ones defined as

$$z_{jt+1} \geq y_{jt+1} - y_{jt} \qquad \forall (j,t) : j \in J = \{1,...,m\}, \forall t \in H = \{1,..., p-1\} \tag{22}$$

$$z_{jt} \in \{0,1\} \qquad \forall j \in \{1,...,m\}, \forall t \in \{1,..., p\} \tag{23}$$

Table 5. Notation of analyzed ILP models

Analyzed optimization models		Model naming		
Model	Description	Without MPs and BG	With MPs (Full Coverage)	With BG (Guaranteed Coverage)
Energy	Basic energy consumption model	ME	ME/FC	ME/GC
Energy Limited Variations	ME+ energy penalty (limiting variations in APs activity)	MELV	MELV/FC	MELV/GC
Energy Guaranteed Powering	At least one powering during single day	MEGP	MEGP/FC	MEGP/GC
Reference Models	All APs permanently powered on with transmission at max. Tx power		RM#1	
	All APs permanently powered on with adaptation of Tx powers		RM#2	
	All APs permanently powered on and BG APs use maximal Tx power		RM#3	

new mathematical model named as *Model Energy Limited Variations* (MELV) has been developed. *Penalty constraints* (22) forces state of the binary variable z_{jt} to be equal to 1 in the case of powering on *j-th* CSs (APs) in subsequent time period, while constraints (23) are the *integrality constraints*. Attaching constraints (18) or constraints (19) to the MELV results in creation of new mathematical models named as *MELV/Full Coverage* (MELV/FC) and *MELV/Guaranteed Coverage* (MELV/GC), respectively.

5.5 Guaranteed powering of network devices

In development of energy saving models, we have also considered the need to keep network element(s) active during some periods, in order to ensure their reliability and to reduce resource wastes. Motivation for this can be found in results presented in paper [13], where authors show that substantial number of APs remains idle during one hour in a day or even during one whole month. The AP idle time indicates how long each AP remains idle before at least a single user associates with some AP. According to measurements performed for two large WLANs, between 50% and 70% of APs has been idle for more than one hour during a day. Moreover, between 5% and 10% of APs remains idle for more than one whole day. Due to long periods of device inactivity, probability of device malfunctioning becomes larger. Also, installed but not used devices present unnecessary waste of network resources disposal in the form of higher capacity, QoS and coverage. To address this problem, we propose one additional model named *Model Energy Guaranteed Powering* (MEGP), through introduction of new *guaranteed-powering constraints* defined as

$$\sum_{k}\sum_{t} x_{jkt} \geq 1 \qquad \forall (j): j \in J = \{1,...,m\}. \qquad (24)$$

Basically, those guaranteed-powering constraints ensures that each CS is powered at least once during one day, and this consequently worth’s for every day during one month. As in the case of the previous model, adding constraints (18) or (19) to the MEGP will result in generation of the new models named as MEGP/FC and MEGP/GC, respectively. Table 5 comprises short description and notation of all analyzed models.

6. Instance generator and reference models

6.1 Generator of input data

In order to test effectiveness of the proposed optimization models, we have developed an instance generator (IG). The IG is able to create synthetic instances representing wireless access network, with the number of CSs and TPs similar to the ones in real networks. Hence, instance of the WLAN described in Section 4.1 is created using the IG. Code of the IG is written in a C++ programming language and is spatially developed for the purpose of generating data used as input data for a CPLEX solver [39]. For generation of input data, the IG takes the following entry parameters:

- *number of the CSs allocated at the BG points, number of the CSs coverage rings with corresponding coverage distances (*m*), PHY rates R_{jkr} (*Mb/s*) of the CSs offered to the TPs in each coverage ring, dimensions of the simulated SA with the sizes of each CA (*m×m*), minimal number of the TPs inside CSs coverage rings, sensitivity threshold of the received power at TPs locations (*dBm*), number and value of the CSs Tx power levels (*dBm*), baseline P_b (*W*) and additional P_k (*W*) power consumption for every of the Tx power levels, values of the constant C (*1/month*) and energy penalty E (*kWh/month*), vertical/horizontal distance between MPs (*m×m*), ranges for definition user demands in CDV (*Mb/s*), overall number (p) of time periods with starting/ending time, and percentage of the active users (TPs) in each time period.*

Based on the number of CSs allocated at the points of BG (Figures 2a, 4b) and maximal coverage radius of each CS, IG calculates dimensions of the SA. Also, IG performs allocation of the TPs inside SA satisfying requirement according to which each TP must be covered with radio signal of at least one CS. Requirement verification has been performed according to relations (2) and (3) of the path loss model. Every of proposed mathematical models have been programmed using AMPL programming language [40], and visualization of analyzed network and obtained optimization results are performed using MATLAB.

6.2 Models for energy comparison

In order to evaluate energy savings obtained by proposed models, *three different reference models* (RMs) have been developed. The RMs are energy inefficient models without possibility of turning off some CSs based on traffic pattern changes. Network energy consumption of these models will serve as the reference value for results comparison. Since each RM has all CSs always powered, the differences between RMs can be found only in the way CSs change Tx power during time periods characterized with distinct CDVs.

First reference model (RM#1) is the simplest model since it assumes that every AP (CS) always transmits using some (maximum) Tx power ($k=1$), independently of the traffic pattern. This approach is equivalent to the most of nowadays WLAN deployments that are based on distributed management, where autonomous APs remain permanently powered (24/7) while transmitting in accordance to a static Tx power settings [41]. Clearly, such approach, although widespread, is totally inefficient in terms of energy efficiency. In the case of network deployment explained in Section 4.1, monthly energy consumption of 61 CS allocated in the SA presented on Figure 1a), can be calculated for the RM#1 using next relation

$$E_{RF\#1} = \left\{ \left[(P_b + P_{k=1}) \times \sum_{j=1}^{m} y_j \right] \times \left[\sum_{t=1}^{p} (T_{t+1} - T_t) \right] \right\} \times C \qquad (25)$$

The same results (Table 2) can be obtained by adding to the ME one new constraint equal to

$$\sum_{j} x_{jkt} = m \qquad \forall (t) : t \in H = \{1,\ldots, p\} \wedge k = 1, m = 61 \qquad (26)$$

This constrains enforce each CS to transmit using highest Tx power level during every time period t.

Reasons for introduction of a *second reference model* (RM#2) are due to new approach in deployment and management of medium/large scale WLANs. This approach is based on implementation of specialized device(s) known as WLAN controller(s), which allows from a centralized location, management and monitoring of enterprise WLANs [41]. One important capability of WLAN controllers is dynamic Tx power control of larger number of continuously powered radio front ends (APs). This peculiarity is primarily developed in order to adaptively ameliorate signal coverage or to enhance network capacity in areas lacking such features. Because of permanent increase in enterprise WLAN deployments with centralized management, the RM#2 fairly simulating energy consumption of such networks is proposed. Again, for consistency, adding to the model ME/FC set of *permanently-powering constraints* defined as

$$\sum_{k} \sum_{j} x_{jkt} = m \qquad \forall (t) : t \in H = \{1,\ldots, p\} \wedge m = 61 \qquad (27)$$

results with emergence of the RM#2. The constraints (27) mandate powering of all 61 CS during every time period t. While remaining powered, CSs can change Tx power levels according to the traffic pattern. Since CSs does not need to transmit solely with the maximal Tx power level, as in the case of previous RM#1 (26), the RM#2 allows some adaptation of consumed energy in compliance to the variations of the traffic pattern. For reference consumptions of the PP1 presented in Table 2, this feature enables the RM#2 to consume 31% less energy during one month in comparison to the RM#1.

In order to define reference energy consumption considering approaches based on the set of permanently powered CSs transmitting with maximal Tx power, *third reference model* (RM#3) has been proposed. Therefore, RM#3 will be very similar to the model ME/GC, only differing in addition of the constraints (27). Short explanation and notation of all RMs have been presented in Table 5. Two sets of constraints (27) and (19) force not only CSs ensuring basic coverage to be permanently powered, but also mandate that all other CSs which do not belong to the set of BG CSs to be active. As the previous RMs, RM#3 also endorse full coverage but with monthly reference energy consumption for 12,8% higher if compared with the RM#2 (Table 2). This is because RM#3 does not allow full flexibility in selection of the Tx power levels as RM#2. Particularly, constraints (19) in the RM#3 forces BG CSs to permanently transmit using highest Tx power level ($k=1$). This reduces overall number of CSs that can adopt Tx power to the traffic pattern, that consequently results in the higher values of reference energy consumption if compared with the RM#2. Nevertheless, monthly reference energy consumptions of the RM#3 is still significantly lower (20,9%) then the reference consumptions of the most energy inefficient RM#1.

Similar conclusions can be obtained for reference energy consumptions of the PP2. Last three vertical bars on Figure 11 presents monthly reference energy consumption of both PPs. Equal values of the reference energy consumption for one month period will be in the case of the RM#1, since both PPs have equal values of maximum instantaneous power (12W). On the other hand, the PP2 has higher values of reference consumption in the cases of RM#2 and RM#3, due to higher value of the P_b (10W) if compared with the one of PP1 (5W).

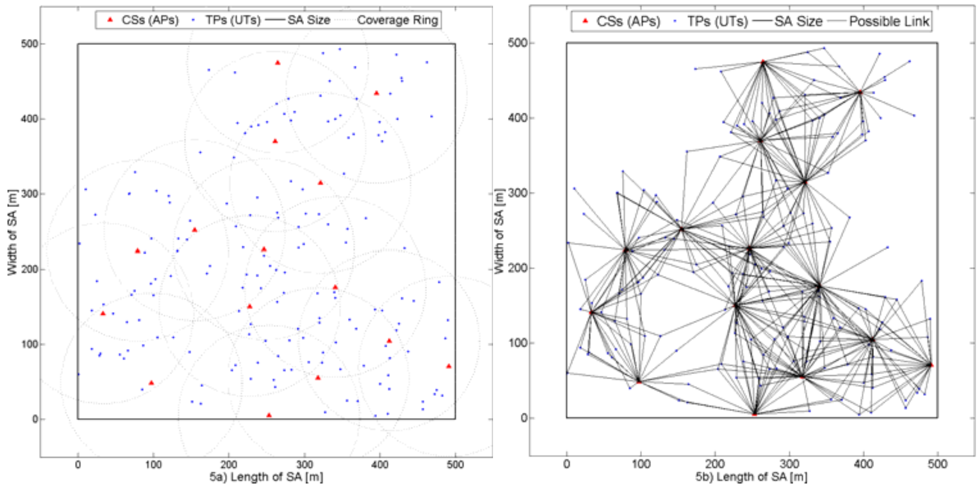


Figure 5a) Structure of the first (Instance_1) randomly generated network instance, 5b) Potential wireless links among network elements

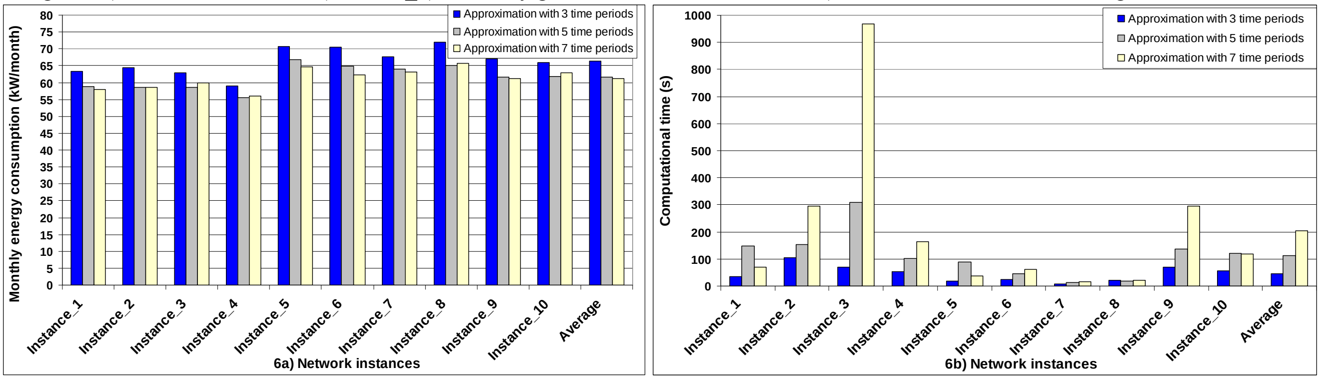


Figure 6. Comparison of: a) monthly energy consumption and b) computational time obtained for three different traffic pattern approximations

7. Numerical results

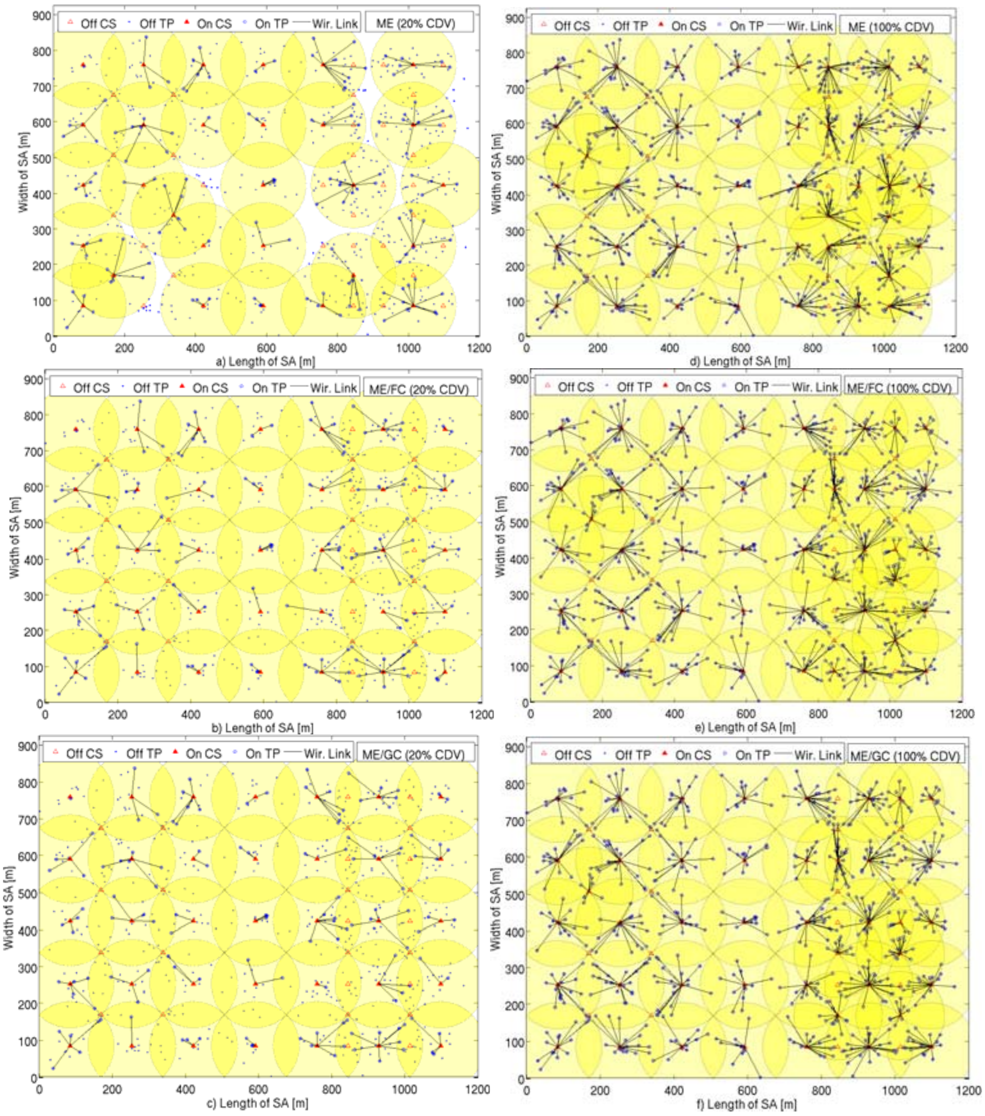
7.1 Results on small instances

To evaluate performance of the optimization framework we have first run our models on ten randomly generated network instances (see Figures 5 for an example). In comparison with the network topology introduced in Section 4 (Figures 1 and 2), analyzed network instances are significantly smaller having 15 CSs and 165 TPs allocated inside SA of 500 m x 500 m (Figures 5). Each of the generated network instances is used for testing performance of the ME for three different traffic pattern approximations (f_{A1}, f_{A2} and f_{A3}) presented on Figure 3. According to Table 3, approximations of the real traffic pattern differentiate in the number of time periods (three, five, and seven time periods in a day).

For each instance and traffic approximation the ME has been solved to the optimum and obtained results in terms of the monthly energy consumption and computational time have been presented in Figures 6a) and 6b), respectively. Lower number of time periods reduces approximation accuracy of the traffic pattern and results in higher monthly energy consumption. This can be seen on Figure 6a) where highest values have been obtained when using three time periods, while lower and very similar results have been obtained with five and seven time periods. On the other hand, approximation with seven time periods generally introduces an increase in computational time, and for some instances this increase is significant (Instance_3). While offering similar results in terms of monthly energy consumption, approximation with five time periods gives solution in lower computational time if compared with seven time periods approximation. For this reason, we considered five time periods t as a good trade-off between computational complexity and accuracy and we decided to use this value in all further analyses.

7.2 Results on realistic instance

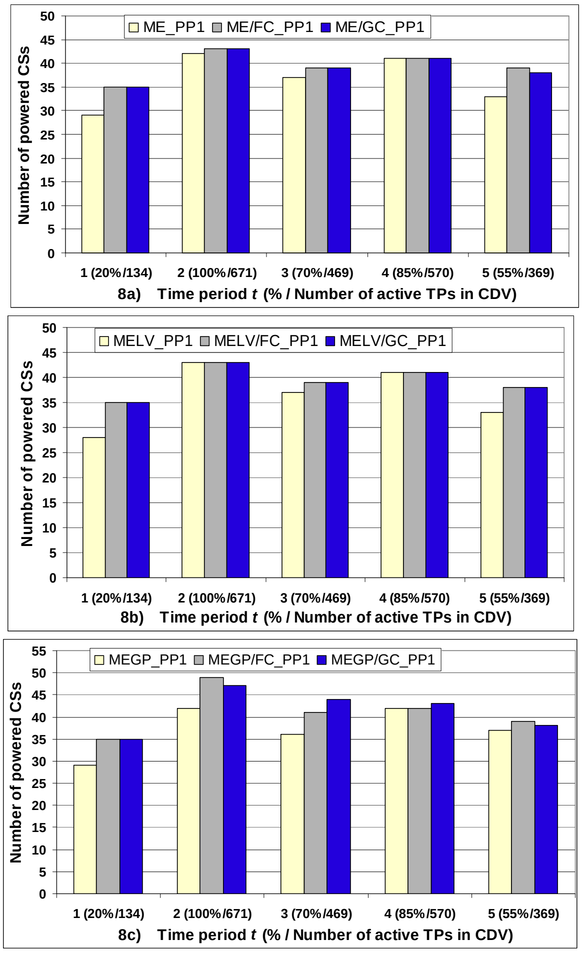
All of the proposed optimization problems are envisioned to be solved at centralized location due to growing trend in deployment of the centrally managed WLAN networks. Although proposed framework can be primarily applicable on enterprise WLANs, ILP formulation of the problem has general structure and with rather small adaptations can be implemented for other wireless access technologies. For models: ME, ME/FC, MELV, MELV/FC, MEGP, and MEGP/FC, optimization process have been interrupted after reaching optimal solution gap between 0,7% and 2,7%. This is because of huge computational complexity of the models and

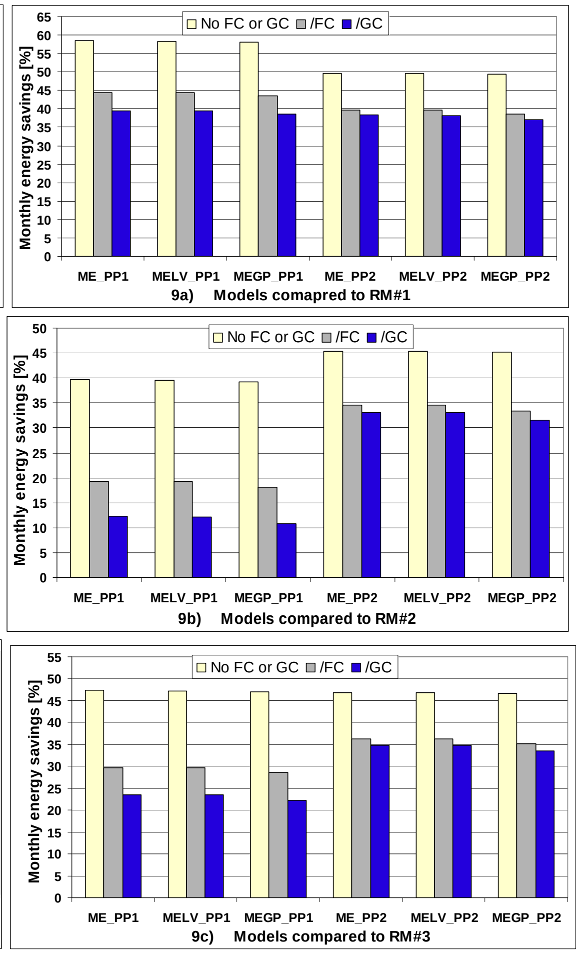


Figures **7:** a), b), c) Optimization results of ME, ME/FC and ME/GC in the case of PP1 for *t=1* (20% of active TPs) and d), e), f) for *t=2* (100% of active TPS)

the size of some of the considered instances that would have required computation times of more than several hours to find the optimum. Because of such small gaps indicating difference between obtained optimization values and expected integer optimal solutions estimated by the solver, it can be said that obtained results are near optimal solutions. This confirms the quality of obtained optimization results in terms of computational accuracy. On the other hand, models: ME/GC, MELV/GC and MEGP/GC have been solved to the optimality, since predefinition of the set of always powered CSs results in somewhat reduced computational complexity. Graphical visualization of the models: ME, ME/FC and ME/GC optimization results obtained for the first (*t=1*) and the second (*t=2*) CDV of the PP1 during a day are presented on Figure 7a), b), c) and Figure 7d), e), f), respectively.

We illustrate results for this CDVs since they constitutes lowest and highest capacity/user demand on network resources, with most noticeable differences in the number of powered on CSs. For every of the analyzed models and for each CDV, positions of all (active) TPs inside SA will be the same, thus enabling visual and numerical comparison of the obtained optimization results. First time period (*t=1*) with the CDV having lowest number (20% CDV) of active TPs will be the most convenient for demonstrating influence of coverage constraints (18) and (19) on visualization of the results. It can be clearly noticed that for such CDV, number and positions of powered on CSs differs between the ME model (Figure 7a)) and ME/FC or ME/GC models (Figure 7b) or c)). Moreover, according to the optimization results obtained for the ME, some parts (white areas) of the SA presented on Figure 7a) remains uncovered with the wireless signal. Size of uncovered area for all models lacking guarantees of complete coverage (ME, MELV, MEGP) varies with a number of powered CSs. Even for the CDV having all TPs active, some border regions of the SA might remain uncovered as presented on Figure 7d). Users in those parts of the SA can not detect network nor they can access to the





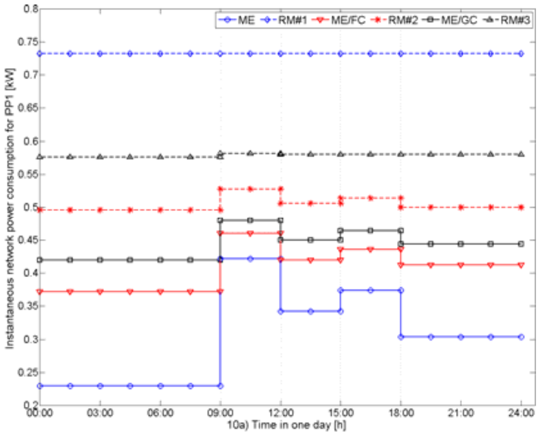
Figures 8: a), b), c) Number of powered CSs in each time period for all models, Figures 9: a), b), c) Monthly energy savings of all models compared with every RM

network resources since they are temporarily turned off. Hence, at any time every part of the SA must be covered with at least one level of a wireless signal. This imposes next important conclusion: without some level of a coverage (cell) overlapping, there will be no possibility for achieving savings in energy consumption of wireless access networks.

Since coverage must be guaranteed for every MP in the SA, introduction of the constraints (18) ensuring full SA coverage, results for the ME/FC, MELV/FC and MEGP/FC with enlargement in the number of powered CSs if compared to the ME, MELV and MEGP (Figures 8). This also worth's for the ME/GC, MELV/GC, and MEGP/GC (Figure 8), since this models, according to constraints (19), have pre-defined number and positions of the permanently powered CSs. Obviously, the need for ensuring complete coverage of the SA with at least one level of the wireless signal introduces significant changes in the network topology (Figures 7a), b), c)), also contributing to the enlargement of the number (Figures 8) of powered on CSs. Generally speaking, statistics presented on Figures 8a), b), c) indicates that higher percentage of active TPs in different CDVs results with higher number of powered CSs, that is also confirmed in Figures 7d), e), f). For all analyzed models, highest number of powered CSs will be during second CDV (*t=2*), since in this time period highest percentage (100%) of active TPs needs to be served. In comparison to the models: ME, ME/FC, MELV, MELV/FC, MEGP and MEGP/FC (Figure 8a), b)), somewhat higher power consumption during few time periods have been obtained as a consequence of the single powering constraints (24). This is also reflected in the total monthly energy consumption (of all analyzed models) presented for both PPs on Figure 11. Nevertheless, Figures 10 indicate much lower instantaneous power consumptions of all models if compared to the reference power consumptions given by each RM. Similar conclusions considering optimization results (number of powered CSs and instantaneous power consumptions) for the same network topology have been obtained for the PP2. Results are not shown here due to space shortage.

7.3 Energy savings

In order to present changes in *energy saving trends* during one day for two PPs, energy savings for every time period of each model have been derived as normalized values compared to the RM#1 and RM#2. Obtained normalized values expressed as



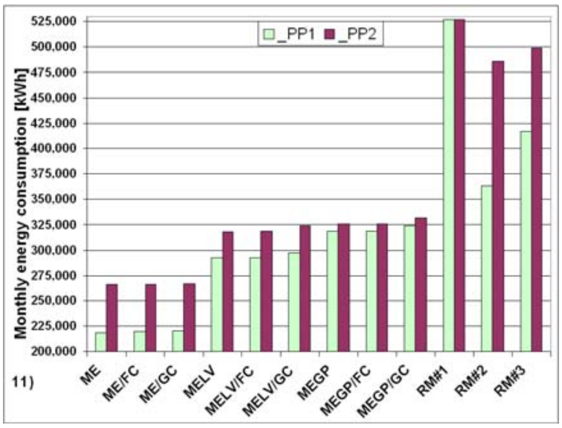
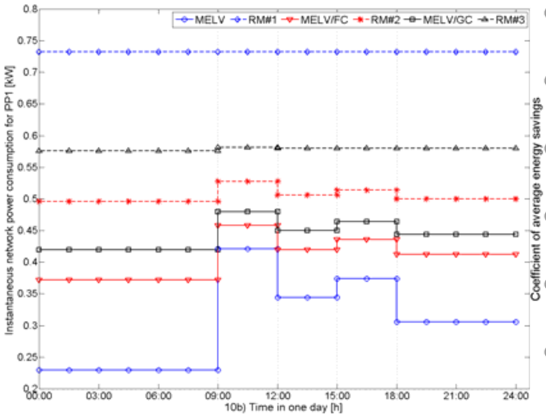
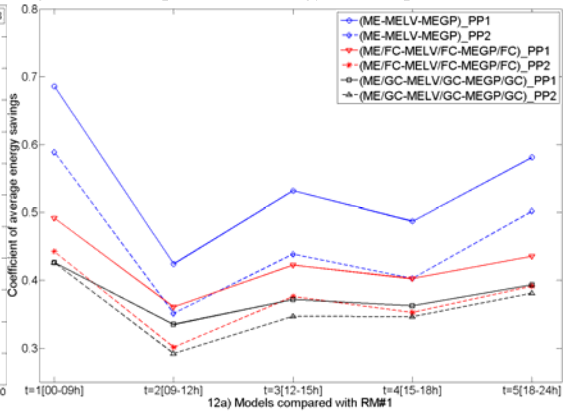
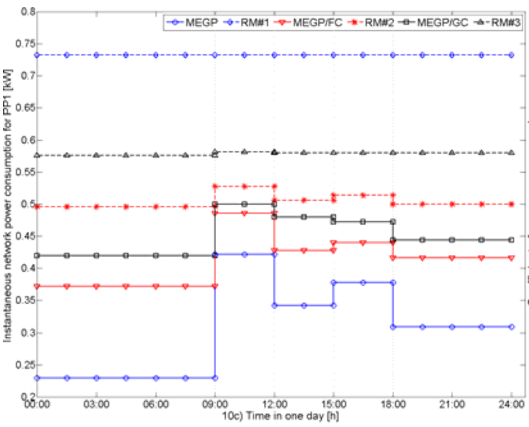
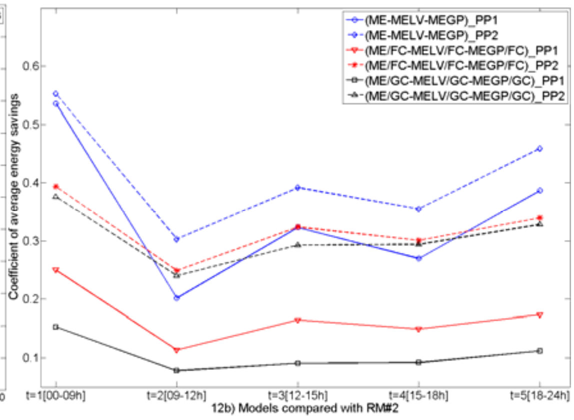


Figure 11. Comparison of energy consumption for all models









Figures 10: a), b), c) Instantaneous power consumption during different time periods, Figures 12: a), b) Energy savings obtained for different PPs during each time period

coefficient of energy savings have been averaged for models offering (ME/FC-MELV/FC-MEGP/FC and ME/GC-MELV/GC-MEGP/GC) or models (ME-MELV-MEGP) that do not offer complete SA coverage (Figures 12). This can be done since similar power consumptions (Figures 10) of compared models during the same time periods results in similar energy savings. In this way we can show influence of different PPs and RMs on possible energy savings during each of five time periods. In the case of comparison with the RM#1 and RM#2, these influences have been graphically depicted on Figures 12a) and b) for both PPs, respectively. In general, a variation in the coefficient of average energy savings during one day follows changes in the traffic pattern. We show higher values of energy saving coefficient during part of the day having lower percentage of active users and vice versa. If we compare coefficient values of the same models and PPs presented on Figures 12a) and b), RM#1 offers higher values of the energy savings in each time period, since this RM is the most energy inefficient RM. Otherwise, the RM#2 as the most energy efficient RM offers lower energy savings (Figure 12b) for each time period during a day. This is confirmed on Figures 9, which also shows that monthly energy savings of the models compared with the RM#3 falls between the ones obtained for the RM#1 and RM#2.

Obviously, selections of the RMs and corresponding reference energy consumption have influence on obtained values of energy savings. Although each of three RMs proposed in this work have background in practical WLAN implementation, slight changes in assumptions considering Tx power management of each RM results with different energy savings. Thus, selection of the RM used for expressing possible energy savings in wireless access networks should be as far as possibly precise in describing energy consumption of a real wireless network. Without realistic RM, it is not possible to have fair estimation of energy savings, which is important for future investments in energy aware network management.

According to Figure 11, every of the analyzed models have higher monthly energy consumption in the case of the PP2. This is expected since PP2 has higher baseline power (P_b) consumption and lower gap between the baseline and maximal power *P(k)*. Still, this is not warranty that models having PP1 will always offer higher values of energy savings. Figures 9b) and c) shows higher percentages of monthly energy savings for PP2 models, when compared with the RM#2 and RM#3, respectively. Although monthly energy consumption of the same model having PP2 is higher than the one of PP1, the values of reference energy consumption are also higher for the case of RM#2 and RM#3 (Figure 11). Because of this, each of the PP2 models objectifies higher energy savings if compared with energy savings obtained with the same models having PP1 (Figure 12b), and Figure 9b), c)). Reverse results have been obtained in the case of comparison with the RM#1 (Figure 12a) and Figure 9a)). In this case, both PPs have equal values of the reference consumption as presented on Figure 11. But, higher values of P_b in the case of PP2 results with lower energy savings of all models (Figure 12a). Hence, gap between baseline (P_b) and maximal power consumption *P(k)* of different PPs will have influence on energy savings coefficient and consequently on total monthly energy savings. As lower value of the baseline power consumption contributes to the enlargement of energy savings, gap reduction between baseline and maximal power consumption also significantly contributes to the lowering of energy consumption. This is something what manufacturers of wireless network devices should take into account during development of future energy efficient network devices.

Percentages of monthly energy savings presented on Figures 9a), b) and c) have been calculated by comparing monthly energy consumption of each model with monthly energy consumption of all RMs. Although ME, ME/FC and ME/GC offer highest monthly energy savings, this models have not background in practical implementations, since they lacks guarantees of complete SA coverage during every time period of a day. For practical realization, more important are results of monthly energy savings obtained for the models with FC and GC extensions. Figures 9 clearly indicate that model FC results, obtained for both PPs, outperform model GC results in terms of monthly energy savings. For example, on Figure 9c) energy savings of the ME/FC, MELV/FC and MEGP/FC for PP1 have been around 28-29%, what is higher in comparison to the savings of 22-23% obtained for ME/GC, MELV/GC and MEGP/GC. Hence, from the aspect of energy savings, network planning approach based on predefinition of permanently powered devices is not the best approach. Although this approach contributes to the reduction of energy consumption, advanced definition of the number, positions and configuration of permanently powered devices reduces flexibility in optimal selection of active network resources. To accomplish optimal adaptation of active network devices to the traffic pattern, network management strategies targeting energy reductions must be completely relieved from any deterministic that anticipates group of a permanently powered devices. This is achieved by network management approach derived in all FC models, where activation of network resources and therefore energy consumption becomes completely adjustable to the user activity.

7.4 Further extensions of the models

Even if the models that we proposed in this paper cover several characteristics of wireless networks, there are a few further extensions that can be easily considered to add specific issues or to simplify the optimization process. For example, when we modeled capacity constraints according to equation (9), we implicitly assumed that different cells do not interfere. This is generally true when several orthogonal channels can be assigned to APs so that interference effect has been mostly avoided. In other scenarios where the number of channels is limited, or even a single channel must be used throughout the network, we can modify the constraints (9) to take into account the effect of mutual interference. The following constraints, for instance, considers all the TPs that are in the coverage area of a given CS when calculating the total traffic, thus modeling the case where all CSs use the same channel:

$$x_{jkt}\sum_{r\in R}\left(\sum_{i\in I(jkrt)} d_{it}/R_{jkr}\right)\le 1 \qquad \forall j\in\{1,\ldots,m\},\forall k\in\{1,\ldots,l\},\forall t\in\{1,\ldots,p\}:\quad I(jkrt)\ne\{\phi\} \qquad (28)$$

Another possible straightforward modification of the model can be that of partitioning the area to be covered into clusters, as suggested in [13]. This basically split the problem into sub-problems and can greatly reduce the computational complexity at the cost of a lower quality of the solutions. Obviously, a similar effect can be obtained designing efficient heuristics to get sub-optimal solutions in reduced computation time.

8. Conclusion

In this paper we have considered the problem of minimizing the energy consumption of a complete wireless access network by switching on and off and adjusting the Tx power of network devices based on the realistic traffic pattern. We have proposed several ILP models that allow to select the optimal network configuration in terms of daily (monthly) energy consumption and to guarantee coverage and enough capacity to serve active users in the SA. Numbers of user and network devices used in analyses correspond to the ones of real WLANs, that gives practical meaning to the obtained results. Presented results show that preserving complete SA coverage at any time contributes to enlargement of the network energy consumption. Furthermore, energy savings in a real wireless networks are only possible if some level of coverage overlapping exist. Besides number of powered network devices, Tx (radiated) power of wireless devices also has significant influence on overall network energy consumption.

Obtained results show that each of the proposed models is actually able to modulate instantaneous power consumption of the network based on the traffic pattern. Also, introduction of additional network management capabilities, like limitation of frequent changes in on/off state or guaranteed powering of network devices during some time period, can be implemented without significant enlargement of the network energy consumption. Presented numerical results show significant savings in the monthly energy consumption when optimized network management based on user activity is implemented. Even for the models that guarantee permanent coverage of complete SA, monthly energy savings reach values of up to 45% if compared with the reference models representing energy consumption characteristic for nowadays WLAN deployments.

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