# WiFi Field Monitoring for E-Pollution Detection

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*Abstract*— **The paper presents an outline of the development of WiFi field monitoring maps using the Internet-of-Things (IoT) technology. The negative impacts of signals generated by the WiFi access points on health and measurement metrics are discussed. The experimental system for collecting WiFi signal data is presented. Finally, the construction of WiFi signal strength heatmap is discussed and some preliminary results using a combination of real worlds and simulated data are presented.**

***Keywords—WiFi; field monitoring, e-health, m-health, s-health, e-pollution.***

## I. INTRODUCTION[1]

Recently there has been a significant increase of the availability of wireless broadband internet access in public spaces. Providers and points of access take the form of municipal WiFi networks, community wireless networks, advanced mobile phone networks (e.g. 4G), and WiFi cafes, restaurants, bookstores and related spaces. The ubiquitous availability of wireless Internet access encourage greater participation in public spaces such as cafes [1] as free WiFi hotspots attract people. The problem is also important in the domain of Ambient Assisted Living (AAL) and other similar domains such as Smart Homes to avoid negative impact of massive use of wireless transceivers for Body Area Networks (BAN), Personal Area Networks (PAN), etc. in terms of daily electromagnetic (EM) exposure to radiofrequency electromagnetic radiation (RF-EMR), ranging between 0 Hz and 300 GHz in frequency, as well as interference emission compliance. In this context the Wi-Fi devices generally work in close proximity to persons, which can lead to higher risks related to electromagnetic field (EMF) exposure [2].

Electromagnetic fields (EMF) of all frequencies is one of the most fastest growing environmental pollutant. All people are now exposed to varying degrees of EMF, and the levels are expected continue to increase in future. Wireless access points (APs) and wireless laptops are also often close to humans. WiFi enabled tablets such as iPads or SmartPhones are handheld and thus provide more radiation directly into human body. The exposure in public spaces and buildings can be even worse than in homes as hundreds of people are simultaneously connecting to the internet.

EMF radiation form industrial grade WiFi systems, which are more than 10 times more powerful as domestic WiFi systems, can penetrate thick concrete block walls. People working in offices or students studying in schools are exposed to 1600 hours of WiFi radiation during an academic year. This value is larger than the 1640 hours of cell phone use in the INTERPHONE study associated with a 40% increase in brain tumors (glioma) [3]. In 2011, the radio frequencies of EMF were qualified by IARC and WHO as possibly increasing the risk of malignant brain tumor [4]. Rats exposed to pulsed digital WiFi frequencies (2.4 GHz) for a long-term (25 months), had a higher rate of both primary and metastatic cancers [5] though other studies did not confirm these findings [6, 7].

WiFi has been linked to electromagnetic hypersensitivity or ‘idiopathic environmental intolerance to electromagnetic fields’ (IEI-EMF). People suffering from IEI-EMF usually have a diverse range of nonspecific physical symptoms (e.g., burning skin, headache, dizziness) that they attribute to their exposure to the EMF emitted by, e.g., mobile phones, mobile phone base stations, power lines and WiFi [8]. There is some evidence of potential adverse effects including headaches, increased blood pressure, and disturbances to electroencephalographic (EEG) activity during sleep [9]. Several papers have been discussing the effects of radiofrequency radiation (RFR) [10, 11, 12]. In 2011, the WHO's International Agency for Research on Cancer (IARC) reclassified RF-EMR as potentially carcinogenic to humans [13]. Also the EM radiation has been called as the fourth pollution source besides air, water and noise [14].

However, long-time effects of these electromagnetic fields on human and animal health are still unknown. Several studies conducted on the effects of RFR on human health have provided contradictory and inconsistent findings regarding the actual health risks associated with RFR [15-22].

Summarizing, when considering the health-related risks of the use of WiFi technology in public spaces there is the need to perform modeling of the locations of WiFi access points in public buildings as well as in private houses to evaluate and minimize the exposure of people to EM radiation while ensuring the quality and signal strength of WiFi connections. Proposing the computational intelligence methods that allow to minimize the effects of e-pollution is a growing research stream [23-29].

This paper presents an initial research towards developing such system using Wireless Sensor Network (WSN) and the Internet-of-Things (IoT) technology.

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## II. RELATED WORKS

A number of systems were developed to support the measurement of WiFi fields both in outside environment as well as in buildings. For example, Bell and Jung [30] used Netstumbler 0.4.0 for detecting available WLAN service and collecting WiFi signal strength data. Netstumbler observes all APs within the wireless card's visible range. Spatial and signal strength data were integrated after data was collected. Chan *et al.* [31] detect the IEEE 802.11b Wi-Fi signal strength and collect into a database. They also create a fuzzy color map to visualize the distribution of Wi-Fi signal. StumbVerter [32] is a wireless visualization tool that relies on Microsoft's MapPoint mapping library. It plots wireless transmitters on a street map using color to indicate signal strength. However, it lacks signal range mapping and it does not provide imagery data. Rensburg [33] use of GPS (Global Positioning System) device, PDA and a tool to measure wireless signal characteristics. Rose [34] describe Argos, the urban-scale WSN designed explicitly to support measurement of ambient WiFi traffic across an entire city. Argos allows urban-scale monitoring of wireless networks. To achieve high spatial coverage, this requires multiple sensor nodes deployed throughout a city that can capture ambient wireless network traffic.

Several large-scale WiFI databases exist, which could be used for researching the harms of exposure to WiFi fields:

- Wigle (http://wigle.net/): a website for collecting information about the different wireless hotspots around the world;
- IGiGLE: Irongeek's WiGLE: WiFi Database to Google Earth Client for Wardrive Mapping (http://www.irongeek.com/);
- Skyhook (http://www.skyhookwireless.com): a database containing unique IDs of more than 16 million wireless routers and their locations.

## III. CHARACTERISTICS OF WIFI SIGNALS

Usually Wi-Fi systems are based on the IEEE Standards 802.11b and 802.11g and operate in the 2.4 GHz frequency band. According to the various local legislations and regulations, Wi-Fi devices which are designed for private (domestic) use should emit low power (less than 20 dBm or 100 mW) and should work in a frequency band also used by other communication devices (such as cordless phones). Wi-Fi devices based on the IEEE Standard 802.11a operate in the frequency band of 5.8 GHz and are suitable to be used in public environment. The IEEE Standard 802.11n works in both frequency bands of 2.4 and 5.8 GHz. Tthe most commonly used technologies are 802.11b and 802.11g (2.4 GHz, maximum output power 100 mW) and the 802.11a (5.8 GHz, maximum output power 1 W).

High frequency (i.e., frequencies from 300 MHz to 3 GHz) electromagnetic fields are mainly human-produced, nonionizing electromagnetic radiations that do not naturally occur in the environment, excluding the cosmic radiation. HF-EMF are present in the environment because of the active development of wireless technology, including mobile phones, Wi-Fi, and various kinds of inter-connected devices making up the Internet-of-Things. Biologic material readily interferes with HF-EMF in a way that depends upon its shape, the conductivity and density of the tissue, and the frequency and amplitude of the EMF leading to an elevation of the tissue temperature and thermal-associated metabolic responses [35].

When RF exposures are taken into account, the main mechanism to be considered is the ability of RF fields to increase an average temperature through the vibration of atoms and molecules in the biological tissue. The heat effect depends on water content of the biological target material, as well as on the frequency and intensity of the electromagnetic (EM) radiation. The characteristic quantity is the Specific Absorption Rate (SAR) [36]. SAR can be calculated as follows [2]:

$$SAR = \frac{\sigma}{\rho} E^2$$

here $\sigma = 10.18$ m/s is skin conductivity, $\rho = 1043$ kg/m3 is skin density, and E is the electric field strength.

Exposure to RF radiation (mainly from mobile phones) has been postulated to trigger a variety of neurological effects, including headaches, changes in sleep pattern, modification in the neuronal electrical activity, and disturbance in the neurotransmitter release [37]. Increasing evidence indicates that oxidative stress may be involved in the adverse effects in the nervous system. Ilhan *et al.* [38] reported a marked oxidative damage in brain tissues of rats exposed to 900 MHz signal for GSM (Global System for Mobile communications) (SAR of 2 $\mathrm{Wkg}^{-1}$ in the brain) for 7 days.

The SAR values are not directly measurable and depend on the frequency. Therefore, so-called reference levels have been defined that are comparatively easy to measure. For the frequency range 0.8–2.8 GHz, the reference levels are approximately 33–62 $\mathrm{Vm}^{-1}$ (general public) and 49–92 $\mathrm{Vm}^{-1}$ (occupational) [39]. Mobile phones are legally limited to a specific absorption rate (SAR) of 2.0 W/kg [40], while most have a SAR of ~1.4 W/kg [41].

## IV. DEVELOPMENT OF WIFI FIELD MONITORING SYSTEM

The system is implemented the following technologies and methods:

1) Internet-of-Things: smart things and devices (e.g. smartphones) that have necessary means to measure WIFI field intensity.

2) Web services. Availability of free web services to share data.

3) Crowdsourcing. A community based effort using contribution of multiple users which

We use a standard three-tiered architecture consisting of:

1) Data gathering layer: a potentially large number of devices that gather information about Wi-Fi field strength and sense it with geodata to the data feeds.

2) Data feed layer that publishes gathered data online for further use by anyone including any applications beyond Wi-Fi mapping.

3) Data aggregator layer that aggregates and integrates all data from data feeds and represents it as a map.

We used Litepoint IQView equipment to measure WiFi signal strength. A LitePoint IQview 802.11a/b/g WLAN tester was used to sample the ISM band at 66 M/s, centered around 2.412 GHz (WLAN channel 1). The Litepoint IQView device digitizes the received signal and records the data onto the laptop using UDP transfer connection. The results were processed using Matlab 8.1 (R2013a) to generate heat map of signal strength.

A computer is connected with the measurement device via UTP cables. Communication with these devices is performed using the TCP / IP protocol. RF connectors are connected to the measuring device using special RF cables. The computer is running agent software for communications with the measuring device and the RF transmitter adjusting system. The system deployment diagram is shown in Fig. 1.

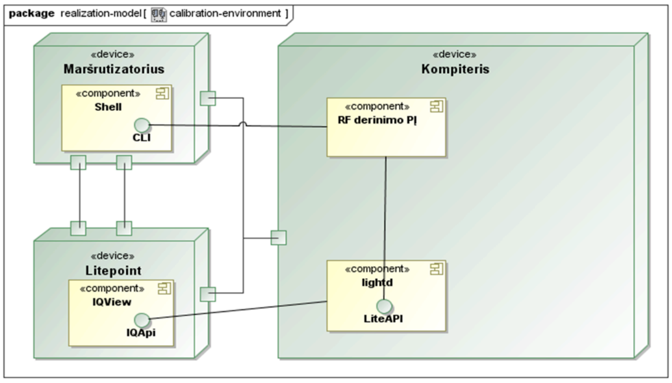

Fig. 1. Package diagram of an experimental system

## V. MEASURED VALUES

Using the developed system prototype we measure: 1) The number of access points visible from a device. 2) The signal strength of the strongest field. 3) Aggregate signal strength.

Attenuation can be defined as the decrease of the amplitude of a signal between its transmission and reception points. As the radio waves propagate through the air it loses power over a distance. Therefore signal strength is less. The loss a signal will undergo between the transmitter and receiver is referred to as Free Space Path Loss (FSPL). FSPL can be understood as power lost as energy disperses into the air. FSPL depends on two parameters: the frequency of radio signals and the wireless transmission distance. The following formula can reflect the relationship between them:

$$FSPL\ (dB) = 20log10(d) + 20log10(f) + K \quad (1)$$

here: $d$ - distance, $f$ - frequency, $K$ - constant that depends on the units used for $d$ and $f$. If d is measured in kilometers, f in MHz, then $K$=32.44.

From Eq. (1), we can find out the distance as follows:

$$d\ (km) = 10\left(FSPL - 32.44 - 20log10(f)\right)/20 \quad (2)$$

The Fresnel Zone is the area around the visual line-of-sight that radio waves spread out into after they leave the antenna. You want a clear line of sight to maintain strength, especially for 2.4GHz wireless systems. This is because 2.4GHz waves are absorbed by water, like the water found in trees. The rule of thumb is that 60% of Fresnel Zone must be clear of obstacles. Typically, 20% Fresnel Zone blockage introduces little signal loss to the link. Beyond 40% blockage the signal loss will become significant.

$$FSPLr = 17.32\sqrt{d/4f} \quad (3)$$

here: $d$ - distance [km], $f$ - frequency [GHz], $r$ - radius [m].

Following the model proposed by Ocana *et al.* [Ocana], the WiFi map can be calculated using a radio propagation model. This model is difficult to obtain for indoor environments, due to multipath effects and temporal variability of the WiFi signal.

$$\begin{aligned} RSL &= TSL + GTX + GRX + \\ &20log(4\lambda) - 10nWlog(d) - X_a \end{aligned} \quad (4)$$

here $RSL$ is the received signal level, $TSL$ is the transmitted signal level, $GTX$ and $GRX$ are the transmitter and receiver antennas gain respectively, $\lambda$ is the wavelength (12.5cm for the 2.4GHz of the WiFi signal), $nW$ is a factor that depends on the walls effect, $X_a$ is a random variable and $d$ is the distance between the emitter and the receiver [42].

## VI. CREATION OF WIFI MAPS

Creating a WiFi signal coverage map for a given transmitter using this approach involves: (1) fitting a semivariogram function, which describes the amount of expected variation as a function of distance between measurements and (2) predicting the value at each unmeasured location (pixel).

Wi-Fi mapping is based on the signal scanning in different places at different times. Ideally, measuring the signal strength of all possible points at the same time allows to obtain the perfect Wi-Fi access point (Access Point, AP) map. However, in practice signal values are measured only in a number of selected location points, while in other points the signal values are interpolated to create large areas of maps. Such WiFi mapping has many uses such as for open access points search; signal versus time comparison; finding the signal problem areas; and optimizing the coverage area.

$\alpha + \beta = \chi.$ (1)

Time signal detection and interpretation must be carried out within the time for all supported frequency band. In order to evaluate the signal quality is assessed the following parameters Signal to Noise Ratio (SNR), and Signal to Interference Ratio (SIR). Since packet data networks are prevalent in wireless networks therefore one needs to assess and receive data transmission at higher layers. Since the higher layers are analyzed to transmit data, so they need to be checked for each channel or frequency after they arrive. Wireless networks have different frequencies each with the further frequency width, which may be 5, 10, 20 or 40 MHz wide. In assessing signal quality is necessary to take into account these parameters. Wi-Fi mapping is necessary to evaluate the signal in different places, and to do so at different frequencies.

The WiFi signal detection procedure is shown in Fig. 2. The data collected can include SSID: Service Set Identifier; MAC address: AP identifier; Signal strength: the access point signal strength; Quality: the strength of the surrounding access points; set of parameters describing the connection quality; Longitude and Latitude of AP coordinates.

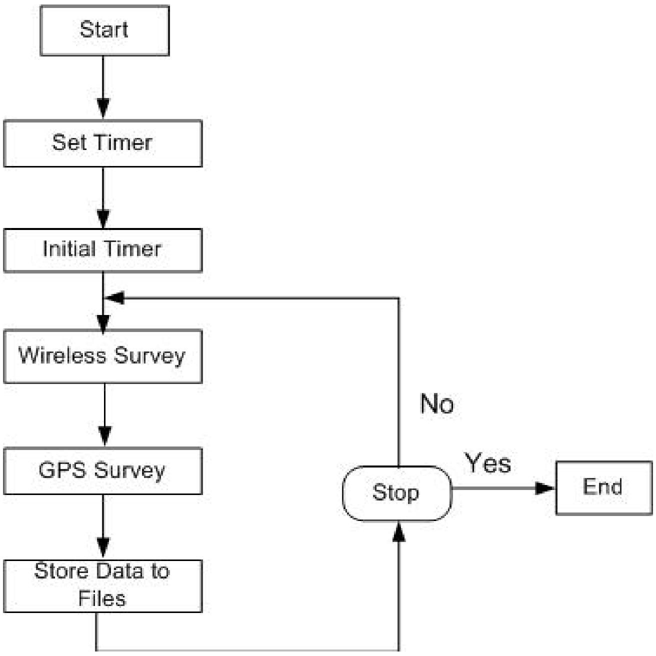

Fig. 2. *Algorithm of WiFi signal capture*

After collecting this data, WiFi maps can be formed in many ways, such as maximum bandwidth, minimum delay, the best coverage, etc. Wi-Fi detection techniques can be divided into two groups:

- Model-based (model-based) uses the detected signals AP locations and radio frequency measurement model as triangulation help from all the points determined by the access point location. This technique has the great advantage of the external mapping. Mapping is a long process, and using this technique, a small amount is sufficient to find enough points with precise AP coordinates. However, the model is unable to assess dynamical changes of AP coordinates at some point in time.

- Radio map (radio-map) constructs a map by measuring the signal strength to a number of points. This technique is used for internal mapping and usually requires 2 stages. The first stage is to collect AP signal strength at predetermined points of location and save them to the database. In the second stage, the signals are compared and the most likely signal at each site used as a good signal for display.

After collecting the data described above is possible the data shown on the map in different ways:

1. Survey Map - signal analysis map to display data collection points and signal strength in these points.

2. AP Signal heatmap – shows signal strength variation in space except only at one selected access point, and all other access points are ignored. Interpolation is used to obtain full map coverage.

3. Signal heatmap - displays the total number of access points and variation of the signal strength in space.

4. AP Coverage – the map divided into zones, featuring dominating point. Also signal strengths are measured, assessing all the signals with a power greater than 70dBm.

5. Frequency, data speeds and other parameters of signal strength maps representative of two or more of the selected attributes dominance zones and overlapping areas in assessing the strength of the signals which exceed the predetermined values.

## VII. RESULTS IN WIFI MONITORING

Due to the small number of transmitting devices in the area, it is not possible to apply simple propagation models, such as free space, to relate the received power to distance. For this reason, we need to consider more complex propagation models accounting for the geometry of the environment. Here we consider the multiwall path loss model [43] which accounts for propagation at 2.4 GHz. It is based on generalization of the classical one slope loss model including an additional attenuation term due to losses introduced by the walls and floors encountered by the direct path between the transmitter and the receiver. The signal power is defined as:

$$M_w = l_c + \sum_{i=1}^{I} k_{wi} l_i + \sum_{n=1}^{N_d} \chi_n l_d + \sum_{n=1}^{N_{fd}} \lambda_n l_{fd} \,, \tag{5}$$

where $l_c$ is a constant, $k_{wi}$ is the number of penetrated walls of type $i$, $l_i$ is the attenuation due to the wall of type $i$, $i = 1, 2, \ldots, I$, $N_d$ and $N_{fd}$ are the numbers of normal and thick doors encountered by the direct path, and $\chi_n(\lambda_n)$ are binary variables accounting for the state (opened or closed) of the $n$-th door.

The data was obtained by the authors within the office building of Kaunas University of Technology (KTU). The experimental results of modeling the SAR values of WiFi signals are presented in Figs. 3, 4 & 5, respectively.

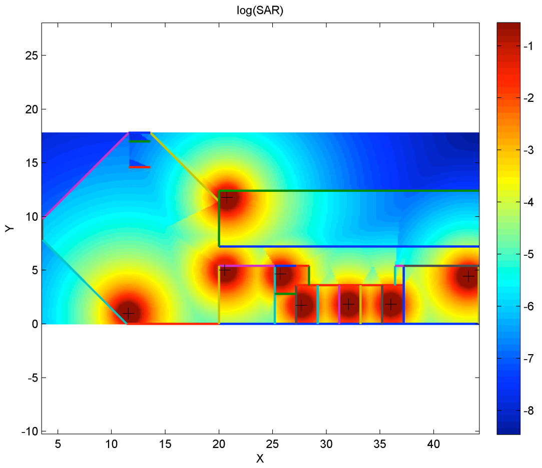

Fig. 3. Example of WiFi signal strength map (with walls)

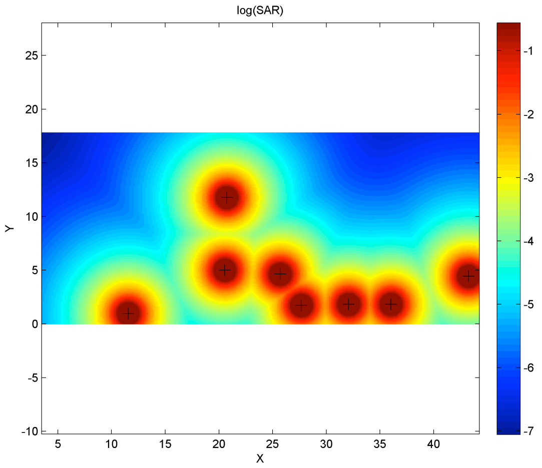

Fig. 4. Example of WiFi signal strength map (without considering walls)

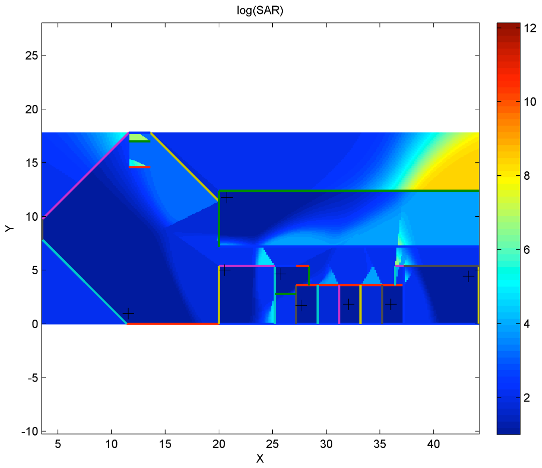

Fig. 5. Example of WiFi signal attenuation map

Finally, we show a difference map between the signal attenuated by walls and other features of the building (Fig. 3) and the modelled signal strength map if the signal would not be attenuated (Fig. 4). These maps can allow us to reveal the locations in the building where the WiFi signals are shielded most by the features of the building thus provided safer locations for office workers, e.g., for placing permanent work places such as office desks (see Fig. 5, see a lighter shaded area at the top right corner of the building).

## VIII. CONCLUSIONS

WiFi needs to be used intelligently due to health concerns. This involves limiting the spatial range of exposure, establishing WiFi-free areas, providing wired access to those who choose not to use wireless, and limiting the duration of exposure in public spaces. The developed prototype allows measuring the WiFi field strength and constructing WiFi signal maps in public spaces. Using such maps one can plan the layout of work desks in offices, or tables in cafes to minimize prolonged exposure to high frequency EM radiation.

Future work will involve expanding the prototype system with the GSM module to allow sending SMS to people's phones to anyone registered, who want to avoid the WiFi hotspots with high levels of EM radiation.

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