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INTELLIGENT CONTROL OF PROPAGATION ENVIRONMENTS FOR INDOOR WIRELESS NETWORKS

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Contents

1 Current State of Research in Intelligent Networks

1.1 Introduction

Whether we like it or not, wireless systems [1] have become a fact of modern life. The vast majority of people living in developed countries use wireless devices on a daily basis. After the "analog" age of radio and TV receivers and mobile phones, a new era of digital devices has arrived. In the beginning, mobile phones and other communication devices were designed as single purpose ones (equipped with single radio). Mobile phones were only able to connect to a single network; laptops only utilized a Wi-Fi connection etc. However, the characteristics of wireless devices have significantly changed during last decade. Users demand their communication devices to do different tasks (send text messages and e-mails, browse the Internet, make conference calls) and, to satisfy customers, the market is loading devices with more and more radios [2] thereby providing consumers with the ability to select an appropriate kind of service depending on actual needs and availability

At the same time, new technologies and standards, such as WiMAX and LTE, provide better, more efficient ways to use and manage wireless resources. These standards, as well as the devices that utilize them, are significantly more complex than their predecessors. Devices known as cognitive radios [3] can control wireless resources by using highly complex algorithms which require defined levels of intelligent behavior such as the ability to observe, learn and, ultimately, make decisions.

The history of cognitive radio (CR) originates from the turn of the century and is, therefore, relatively short. Most published work deals with what is known as spectrum sensing CR which focuses on dynamic spectrum access (DSA), spectrum sensing and sharing [4]. The concept of DSA stems from the fact that certain parts of the licensed spectrum are, in a given time and place, underused and therefore could be exploited by CR device. In this particular case of CR, the only observable parameter is radio frequency spectrum. DSA CR continuously observes, learns, plans and makes decisions based on frequency spectrum.

When we extend the range of parameters which can be observed and taken into account by CR to any observable characteristic, we define the Ideal (Mitola or Full) Cognitive Radio (iCR) [3]. An iCR contains DSA CR and observes radio environment, and, in addition, can monitor and consider any determinable variable such as user behavior, position, speed and acceleration, current time, temperature and use this information during cognitive process consequently.

1.2 Smart Environments

Generally speaking, the Smart Environments concept [5] is a technology providing people located in indoor premises with services making their lives more comfortable. In fact, it is a small world, where devices continuously work together and cooperate to make the inhabitants' life as easy and pleasant as possible. Users in such systems can avoid activities which they normally have to do by themselves. These activities can be done by devices working within the Smart Environment system using remote control or even automatically.

The system is able to observe, decide and act, and learn. Such behavior requires a certain degree of intelligence and some principles are similar to the Cognitive Radio architecture.

The progress in areas of computing, machine learning and sensor networking within the last decade has allowed this idea to become a near-reality. The information mentioned here is not comprehensive and is within the scope necessary for our work. Many papers and books deals with the SE and more information can be found in [5, 6].

The basic difference between a simple remote controlled environment and a Smart Environment lies in the ability to model users' behavior. Without this characteristic, SE cannot be considered as smart. Each SE system should have the following basic features [5, 7]. Some of them are highly similar to the iCR concept.

- **Remote Control of Devices**
- **Device Communication**
- **Sensory Information Processing**
- **Predictive and Decision-Making Capabilities**

1.3 Controlling Coverage in Smart Environments by Using Active Frequency Selective Surfaces

It is widely known that the behavior of electromagnetic waves inside buildings is chiefly determined by both the building geometry and material properties of the building components (walls, floors, ceilings, etc.) [8] and any change made in the geometry of the scenario has an influence on the propagation environment [9]. The aim of the controlling techniques is to influence propagation environment in a positive way – to limit interference and improve system performance.

It was shown that there are several possibilities to improve the propagation environment using additional materials mounted on the existing walls [10-12]. Most related work deals with techniques utilizing FSS [13, 14] or, less frequently, combinations of reflectors and absorbers [15]. The FSS in the form of thin films could be retrofitted to building walls making it possible to improve system performance in existing buildings [14, 16]. It can enable multipath propagation to be better controlled and to focus energy towards specific parts of the building (while avoiding interference to an electromagnetically-sensitive area).

An example of the FSS without the wall substrate was presented in [17], and this active FSS was designed at a frequency of 2.3 GHz (Fig. 1.1). At this frequency, if the bias of the diode is set to OFF (OFF state) we can obtain a surface which is almost transparent, i.e. almost all impinging energy passes through the FSS – the transmission and insertion loss is nearly zero. If diodes are switched on (ON state), high isolation is achieved and in the sample surface types used here the majority of impinging energy is reflected, and the isolation level is about 25 dB (transmission loss is therefore 25 dB).

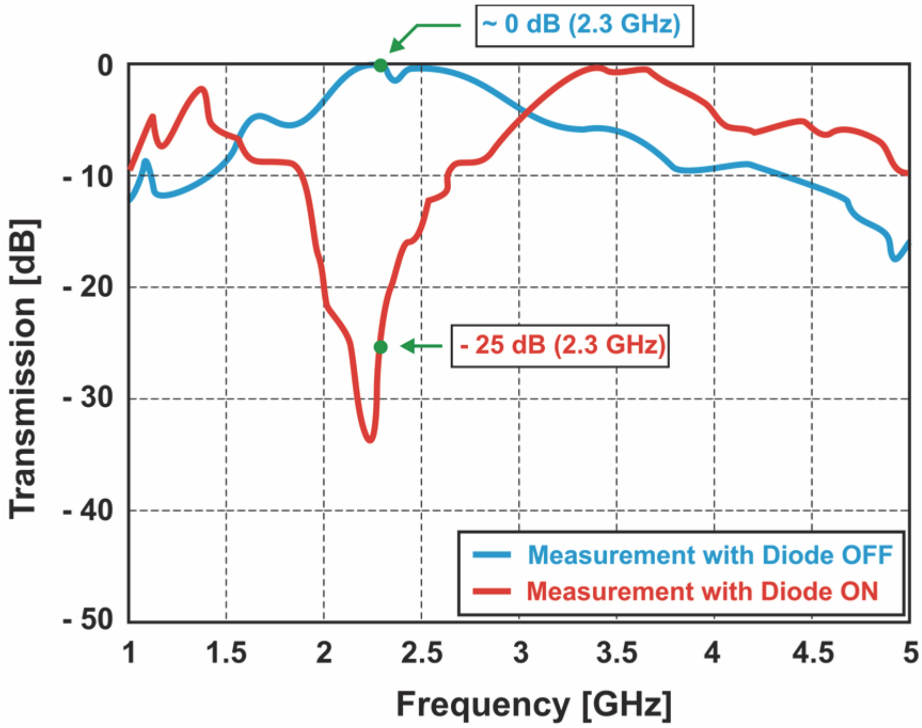

Fig. 1.1 Frequency characteristics for ON and OFF state of active FSS presented in [17]

2 Propagation Prediction Techniques for Indoor Smart Environments

Indoor Smart Environments [5], like all common indoor premises, can be complex scenarios consisting of many objects having a significant influence on the propagation of electromagnetic waves. It goes without saying that modeling of electromagnetic wave propagation is a difficult task. Precise propagation prediction is a crucial part of Smart Environments design, especially when controlling coverage.

Many models for indoor propagation predictions have already been proposed [1, 8, 18]. There are many possible classifications of these models, but two basic groups are usually identified. One group, the empirical models (e.g. One Slope Model [19]), utilizes relatively simple formulas containing empirical parameters to estimate path loss and therefore do not require a database of exact positions of obstacles. They provide rapid predictions, but due to their relatively simple principle of function they cannot achieve a high level of accuracy. Other group, the deterministic models, (e.g. Full-wave, Ray-optical models or Moment-method models [19]) is based on an approach requiring an accurate and complete database of obstacles including their material properties. This approach uses a rigorous description of electromagnetic wave propagation, which is, unfortunately, characterized by high time consumption.

Aside from the two model categories mentioned above, we can distinguish two other groups of models which cannot be classified into either of the basic categories as they use a combination of deterministic and empirical approaches which we refer to as semi-empirical and semi-deterministic models. Semi-empirical models (e.g. Multi-Wall Model,) benefit from a speedy empirical approach, but in contrast to pure empirical models, account for materials and the position of obstacles. Semi-deterministic models (e.g. Motif Model [20], Dominant Path Model [21]) represent a compromise between time-consuming deterministic models and less accurate empirical models. Generally speaking, the semi-deterministic models use a rigorous physical approach which is, in contrast to deterministic models, simplified in certain respects.

3 Objectives

The main aim of the doctoral thesis is to extend the idea and concept of the ideal Cognitive Radio and Smart Environments using intelligent infrastructure. That means to suggest and verify functionality of a new concept of intelligent control of propagation environments. This will be done through the development of static system simulator of Smart Environments utilizing Intelligent Walls. Further aim of the thesis is to develop a site-specific semi-deterministic model, whose features will meet all requirements of the system simulator modeling an autonomous cognitive network and which will be considered as a part of the system simulator.

A step-by-step progress will be as follows: first of all, we need to design and develop new principles of fast semi-deterministic approach, which will be implemented into a computer code and a new propagation model will be created. After the implementation of the principles, the new model will be tested and evaluated and its proper functionality will be verified based on measurements. Later, a new possible part of the iCR will be suggested. Basic concept of the controlling coverage using Active Walls (AW – common walls equipped with active FSS) will be presented and investigated. If a positive influence of the concept is proved, the autonomous wireless cognitive network system utilizing Intelligent Walls will be developed. Finally, the cognitive system functionality and performance will be evaluated and verified. All the above mentioned system simulations will use the new propagation model as a source of coverage data.

We can summarize main goals of the doctoral thesis as follows:

- To develop and verify a new semi-empirical model for electromagnetic wave propagation predictions in Smart Environments
- Further, to outline a new concept of Cognitive Radio – intelligent controlling coverage in indoor scenarios using Intelligent Walls
- Finally, to develop and verify a basic static system simulator incorporating a new model as well as principles of the new concept of the cognitive radio - intelligent control of the propagation environment forming an autonomous wireless cognitive network system increasing the system performance.

4 New Semi-Deterministic Model for Electromagnetic Wave Propagation Modeling in Smart Environments

The aim of this chapter is to present a propagation tool utilizing a 3D site-specific model considering all significant physical phenomena (penetration, reflection, diffraction and diffuse scattering) while providing both narrowband (signal coverage) and wideband predictions (delay profile, AoA), thus enabling detailed designs of indoor scenarios and fast semi-deterministic calculations based on a simplified approach. Unlike many other site-specific models , our model does not require a database of material properties which form obstacles in a scenario as the material properties are replaced by a few probabilistic parameters which are optimized by means of a measurement campaign.

4.1 Basic Principles of New Model

The new 3D semi-deterministic model combines both stochastic and deterministic approaches. This model is partly based on the 2D Motif Model [20]. Let us describe some of the main features of our model. The deterministic part employs ray-based algorithms respecting the exact position of the walls in a scenario while the stochastic approach is used to solve the interactions between the rays and the walls. The stochastic parameters are calibrated by measurement data, which means that Fresnell equations and other complex computations can be replaced with a fast empirical approach while phenomena such as diffuse scattering and reflection are considered. At the same time, there is no need to know the walls' electrical properties. This is significant since it is problematic to define the material parameters and roughness of the walls. On the other hand, an efficient way to calibrate the model is to measure received power in a typical (primary) scenario with the given structure, tune the probabilistic parameters and then predict propagation characteristics for scenarios of similar type (secondary scenarios).

4.1.1 Ray Launching

The model is based on the modified Ray-Launching method. Models belonging to this group substitute electromagnetic waves with a high number (an infinite number in an ideal case) of plane waves which are usually represented by their directional vectors/rays. Rays are launched from the transmitting antenna according to an antenna radiation pattern converted into a pattern determining the number of rays that are launched in specific directions (the so-called "launching pattern"). All the rays then carry the same part of overall power given by the relation.

Once a ray is launched from the transmitter, the intersection with an obstacle is found and the angle of arrival is computed. The subsequent direction of the impinging ray is determined by means of what is referred to as a probability radiation pattern (PRP).

4.1.2 Probability Radiation Pattern

To describe the PRP in more detail, it is a function of the direction of the AoA (both the azimuth and elevation) and probabilistic parameters defining the wall properties. It does in fact determine the probability of the subsequent direction of the impinging ray (expressed in terms of the spatial angle) for each specific AoA (Fig. 4.1c). This implies that a single new ray is generated instead of the impinging ray and therefore the number of rays considered does not increase (in contrast to an absolutely rigorous approach where thousands of rays with different amplitudes would need to be generated). The maximum of the PRP therefore represents the most probable direction of the new ray. Consequently, it helps to decrease the time needed for computation and saves computer memory.

The above-mentioned overall PRP is created under Phong's law [22] on the basis of three probabilistic parameters. It has been shown that the reflected light consists of two main components, namely the diffuse reflection (directional part – Fig. 4.1a) and the omnidirectional diffuse part (Fig. 4.1b). If the surface under consideration is perfectly smooth and reflective, Snell's law holds that only the specular ray is reflected. This assumption cannot usually be satisfied and, in view of this, the diffused component should be also taken into account.

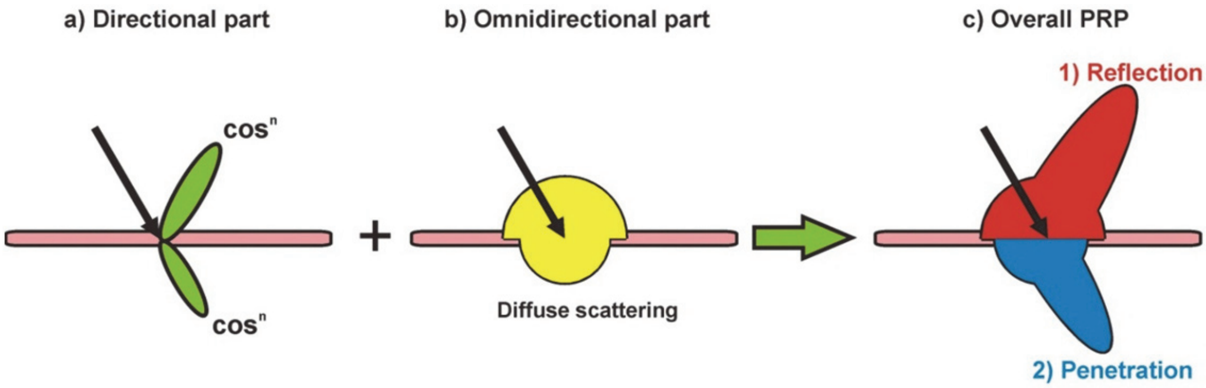

Fig. 4.1 An example of the PRP formation (probability vs. angle)

Each type of wall in the scenarios is described simply using only three probabilistic parameters - the probability of absorption, reflection and diffuse scattering - which express the three basic phenomena of wave propagation in straight tunnels: reflection, absorption and diffuse scattering. The values of these parameters form the shape of the PRP and depend on the material properties (material constants, width and roughness of the wall for the specific frequency), dimensions and polarization.

4.1.3 Iteration Algorithms

When the ray impinges on the wall, the corresponding PRP (Fig. 4.2a) and equivalent Distribution Function (DF) are generated on the basis of the angle of arrival and the three probabilistic parameters defining the wall.

After the creation of PRP (Fig. 4.2a) and corresponding DF (Fig. 4.2b), a random number is generated and the next direction of an impinging ray is determined using the DF. The range of random numbers for DF depends on the requested angle resolution.

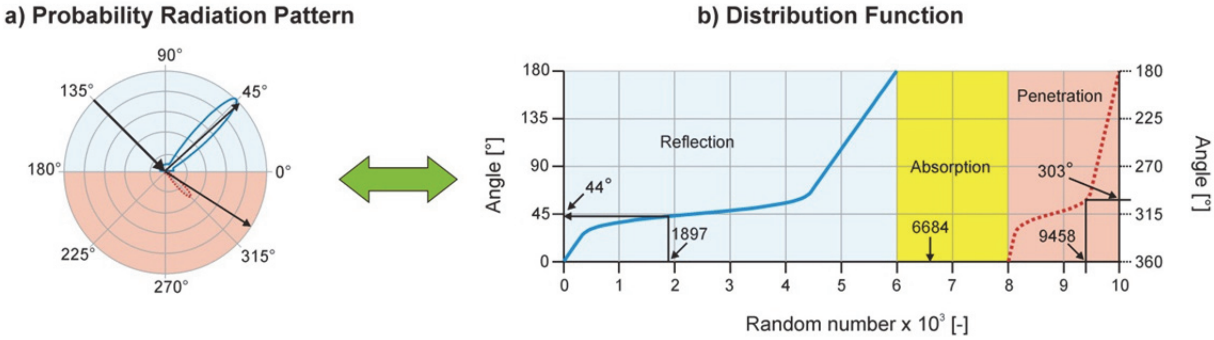

Fig. 4.2 Determination of the next direction of an impinging ray

After the ray leaves the wall in its new direction, the next intersection is again computed and the interaction is solved. This is repeated until the ray is absorbed or leaves the scenario.

When a sufficient number of rays have been launched (and the requested precision and range has been achieved), the scenario is divided into a cubical grid and an average signal level in each grid element is computed according to (4.1). If a high number of rays is launched, then the signal level in each grid element is proportional to the number of rays passed through this element. The averaged received power is therefore given by:

$$P_{REC} = \frac{N_{RPT}}{N_{LR}} \cdot P_{TRANS}\,, \tag{4.1}$$

where P_{REC} represents averaged received power (W), N_{RPT} number of rays passed through the grid element (-), N_{LR} number of launched rays (-) and P_{TRANS} overall transmitter power (W).

4.2 Verification of the Model by Measurements

As mentioned earlier, the model relies on measurements providing data needed for the model calibration. Although a measurement campaign is the most accurate method to calibrate the model, it has one significant drawback – it can be time consuming and, therefore, costly making it impossible to perform a measurement on each scenario examined. A more effective way is to choose a typical indoor scenario (primary scenario), calibrate the model using measured data to obtain a "universal" set of materials as a result of optimization process.

As the primary scenario, we chose a floor in our university building for which (Fig. 4.3) we already had a detailed floor plan and approximate information about wall materials. Floors inside a hotel (Diplomat hotel in Prague – Fig. 4.4a) and commercial office building (Koospol company – Fig 4.4b) were chosen as secondary scenarios due to limited information on the floor plan and wall materials. To verify the function of our propagation tool, a measurement campaign inside the primary as well as secondary scenario was carried out [23].

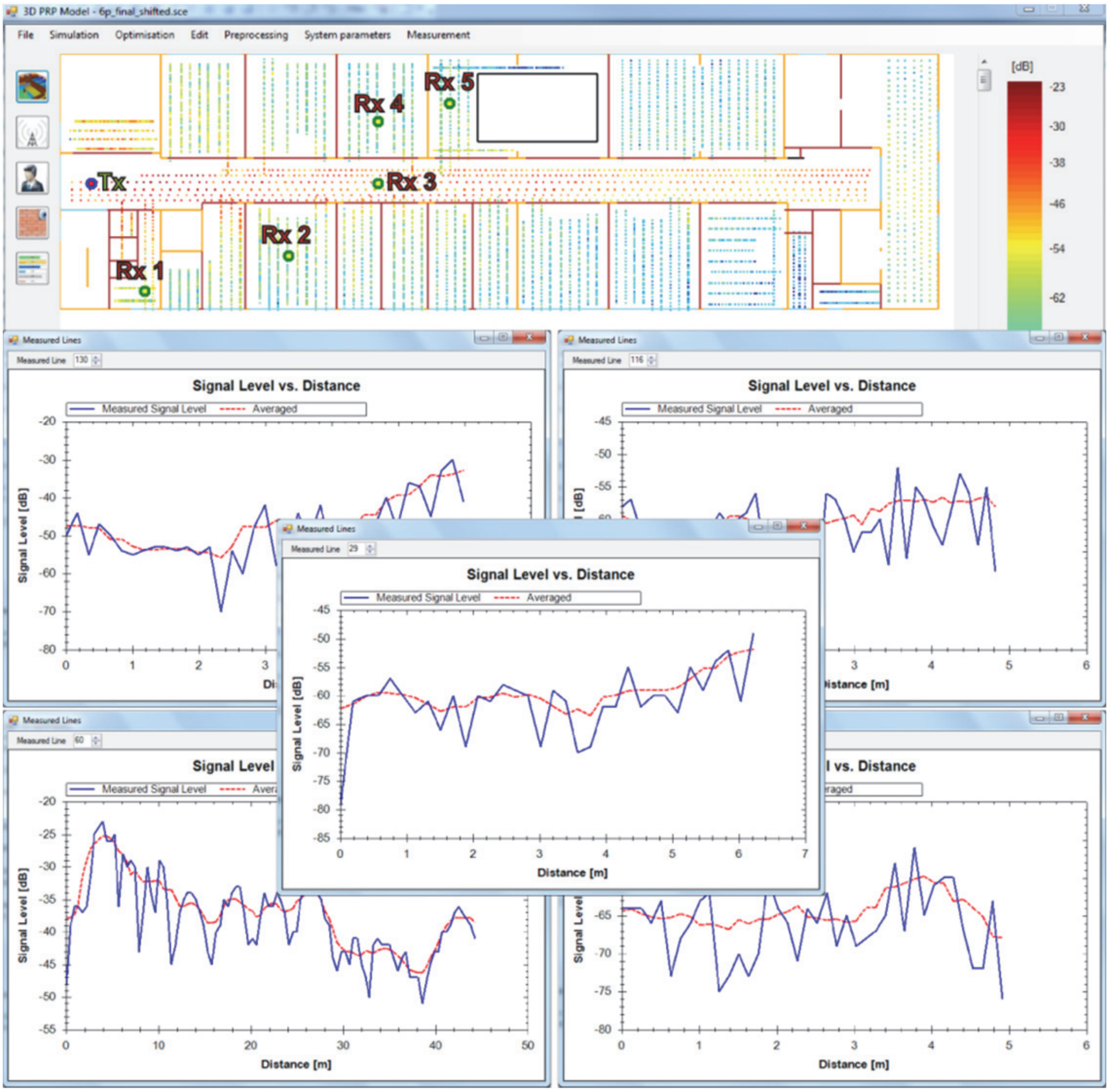

Fig. 4.3 Measured data as displayed in the prediction tool (primary scenario)

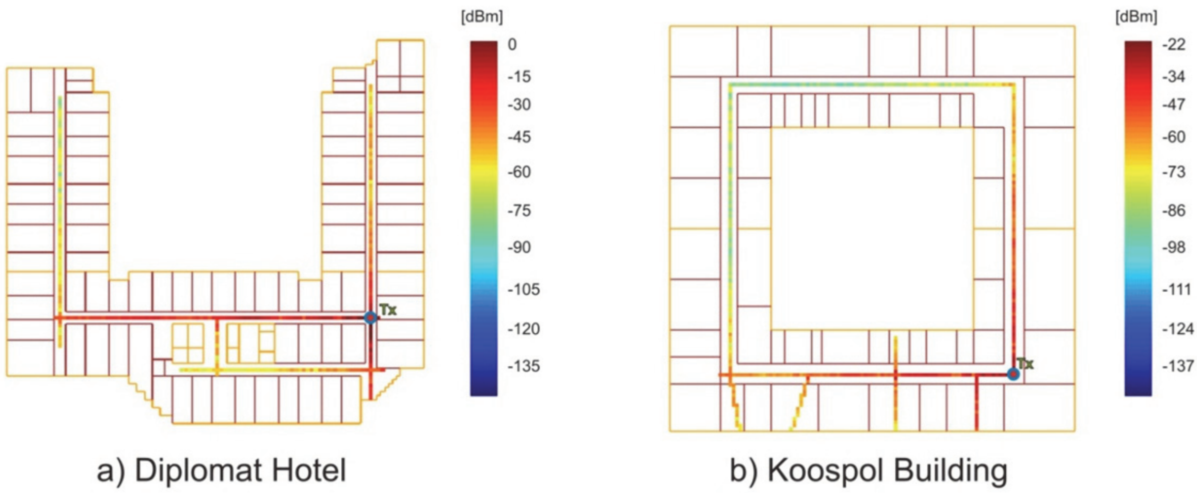

Fig. 4.4 Measured signal Coverage in the Diplomat hotel and Koospol Building

Model Calibration

The genetic evolutionary algorithms were used for the model calibration. The resultant obstacle parameters are shown in Table 4.1. The probabilistic parameters were set automatically by using an optimization algorithm; diffraction distance was set, in advance, to 3 λ which is approximately equal to the size of the grid used for predictions (0.5 m).

Color	Type of Wall	p_A [-]	p_{DS} [-]	p_{RT} [-]	D_{DIF} [λ]
	Light Wall	0.31	0.12	0.91	3
	Heavy Wall	0.6	0.8	0.14	3
	Glass	0.21	0.24	0.03	3
	Metal	0.04	0.58	0.41	3
	Floor & Ceiling	0.19	0.30	0.36	3

Tab. 4.1 Optimized probabilistic properties of obstacles

Signal coverage provided by simulation was compared with the averaged measured data (Fig. 4.3) with the mean value of the difference between predicted results and measurement being -0.02 dB and a standard deviation of 6.91 dB. This demonstrates that the results provided by our model are in good agreement with the measured results. The best agreement is reached at points where receivers are located and conversely, the worst agreement is at points far from receivers.

The optimized values of probabilistic parameters were also used for the other two scenarios (figures 4.4a and 4.4b). As we did not have a detailed plan showing the position of walls, windows or information about materials, we modeled the scenarios using only two kinds of materials – light and heavy walls. Table 4.2 shows a comparison among accuracy levels for each scenario expressed by the mean value and standard deviation of the difference between measured data and simulated results, in addition to the time needed for computation. It is necessary to mention that we used a 3D ray launching algorithm with no form of post-processing or optimization of number of rays for the comparison.

Scenario	Mean [dB]	Deviation [dB]	Time [s]
CTU Building	-0.02	6.91	192
Diplomat Hotel	2.34	8.15	336
Koospol Building	4.12	9.67	326

Tab. 4.2 Stochastic comparison of differences between simulations and measurements

The lower levels of accuracy were achieved for the Diplomat Hotel and the Koospol building (i.e. secondary scenarios) in comparison with the primary scenario which was optimized on the basis of measured data. Although mean values of difference, as well as standard deviations, indicate that probabilistic parameters optimized for the primary scenario (and used for secondary scenarios) provide slightly lower performance than comparable models [24] (deviations between 5 and 8 dB), it can be considered as a satisfactory performance with respect to the fact that a database of exact obstacle positions and material properties was not available and only approximated positions of obstacles were taken into account.

5 Intelligent Control of Propagation Environments for Indoor Wireless Networks

The purpose of this chapter is to introduce and evaluate the concept of an Intelligent Wall, or, a system of multiple Intelligent Walls, which was evolved as an autonomous part of a Smart Environment utilizing active frequency selective surfaces. The concept is based on the fact that signal coverage and interference levels in indoor premises are strongly influenced by the position of obstacles (mostly walls) and their material properties. If the system affects the obstacle parameters, it can consequently influence radio channel parameters and have a crucial effect on the system performance including signal coverage and interference. The position of the walls cannot be changed dynamically in contrast to the wall material properties. This can be achieved by using the active FSS as a spatial frequency filter. The Intelligent Wall is able to continually observe the environment, make decisions and learn autonomously from past experiences based on sensors and a Cognitive Engine with machine-learning control algorithms.

5.1 Intelligent Walls as Autonomous Parts of Smart Indoor Environments

5.1.1 Basic Principles

As was already mentioned, the main goal of the IW is to dynamically turn the active FSS on or off in order to change its electromagnetic characteristics thus affecting the propagation environment and subsequently the system performance. In our test case implementation the IW is designed as a part of the self-configuring and self-optimizing system consisting of a pre-installed collaborative autonomous infrastructure. It can be a common wall or multiple walls equipped with an active frequency selective surface, simple low-cost sensors [5] giving estimated information on the users' space distribution and a Cognitive Engine.

The environmental observation based on sensors is supplemented by feedback from the network providing information of actual system performance such as the throughput and number of active users of each base station. This allows decision making and learning towards the continuous optimization of the system performance by changing the propagation environment with the help of FSS.

If the CE can switch individual Intelligent Walls on and off while collecting information on the users' position, together with the parameters expressing system performance, it can obtain a set of data suitable for learning. After the system has learnt from the previous experience, CE can control the propagation environment autonomously. The decisions are then only based on the data gained from sensors. The learning process is described in detail in section 5.3.2.

5.1.2 Sensors

A low-cost sensor in the form of a simple receiver consists of a receiving antenna, detector and an evaluation circuit that estimates the number of users in its vicinity. The antenna performs as a planar patch antenna with a hemispherical radiation pattern. Thanks to its flat design, it is suitable for mounting on a wall. Detector and evaluation circuits turn the received signal into a form of digital information on received power level and this information is then transferred to the CE of the IW.

In our simplified approach, we assume all active users are transmitting a pilot signal with constant low-power level. The sensor receives and integrates the power transmitted by users which is, of course, influenced by the distance between a user and the sensor and all obstacles between them. The sensor therefore provides information on received power level which is proportional to the sum of power received from different users and corresponds to the number of users in the sensor's surroundings and their distance to the sensor.

5.2 System Level Simulations

5.2.1 Simple Static LTE Simulator

The concept of the Smart Environment utilizing Intelligent Walls is simulated and verified using static snapshot simulations of a downlink for a generic OFDMA system. Some of the system parameters were selected based on the LTE system [25-27]. The goal is to demonstrate the influence of IWs on the system performance so that the complexity of the simulator is limited to elementary functionality only. Essential issues for realistic simulations of specific wireless systems such as handover, scheduling, power control, protocols, coding, etc. are not taken into consideration.

Downlink Throughput Determination

On the basis of the simulations described in [25], spectral efficiency depending on the given modulation can be determined. The dependence between spectral efficiency and Signal to Noise and Interference Ratio (SINR) can be approximated by the following relation, which is based on the attenuated Shannon capacity of the channel [27]:

$$C = 0.65 \cdot \log_2(1 + SINR), \qquad \text{for } SINR \text{ in [-8; 17.7] dB} \qquad (5.1)$$

where C represents the spectral efficiency [bps/Hz]. C is equal to 0 if $SINR$ is less than -8 dB, and equal to 3.83 bps/Hz if SINR is greater than 17.7 dB.

Our Test Case Network Implementation

For our test case of a simple LTE network, we chose an approach based on the above-mentioned simulations, since the theoretical approach doesn't take into account some of the real-channel issues.

The test case network consists of BSs sharing the same carrier frequency of 2 GHz and 10 MHz bandwidth and, therefore, can be sources of mutual interference. We considered the 180 KHz width of the resource block (RB) which implies that each BS can provide users with up to 50 RB. The constant output power of 24 dBm is chosen instead of a dynamic power control in order to not influence the simulation results. The modulation scheme used for the communication between a BS and an active user is determined by simulations of

SINR. BSs can utilize three basic modulation schemes – QPSK, 16QAM and 64QAM with changing code ratios according to the current conditions in the radio channel. We also presume the AWGN channel and SISO antenna configuration.

User's throughput is given by the spectral efficiency and the user's bandwidth which corresponds to the number of RB provided. Overall system throughput is given by the sum of users' throughputs:

$$T = \sum_{i=1}^{k} 180 \times 10^3 \cdot N_i \cdot C_i \; , \tag{5.2}$$

where *T* represents the overall system throughput [bps], *k* the number of active users, N_i the number of RB provided to *i*-th user [-] and C_i spectral efficiency of the *i*-th user [kbps/Hz].

The users' throughput, as well as the overall system throughput, can be determined on the basis of relations (5.1) and (5.2), respectively.

5.2.2 Test Case Scenario

We selected a single-floor scenario representing a small conference center. The 40 x 40 m floor plan (Fig. 5.1) consisted of two meeting rooms and a coffee break area connected by a corridor. The inner partitions of the scenario represent a system of two IWs with sensors. The wall properties for the propagation modeling are shown in Tab. 5.1 including ON and OFF parameters of the IWs. The parameters were derived as a combination of a common wall and active FSS. For the sake of simplicity, the doors and windows were not considered in the scenario even though the influence of these components is not always negligible [9] so it might reduce the performance of IWs.

Part of building	Material	Thickness [cm]	Transmission Loss [dB]		Reflection Loss [dB]	
			OFF	ON	OFF	ON
External wall	Concrete	30	17.27	-	7.51	-
Light wall (IW)	Plaster Board +FSS	5	2.18	27.18	12.90	1.82
Floor and Ceiling	Concrete	10	6.89	-	7.51	-

Tab. 5.1 Material properties

The coffee break area (CBA) and meeting rooms are separated by two IWs (IW1 and IW2) with active FSS and 28 sensors (S1 – S28) on both sides. Both IWs can be either switched off or on. It implies that the four configurations of the Intelligent Walls can be set according to the decision of the CE: both walls in the ON state (configuration 11), both OFF (00), IW1 OFF and IW2 ON (01) and vice versa (10).

The scenario contains three BSs – two wall-mounted BSs are placed in the meeting rooms and equipped with directional antennas to cover the meeting rooms. The third BS is located at the boundary between the corridor and CBA and is connected to a typical indoor ceiling-mounted omni-directional antenna to cover the long corridor and CBA.

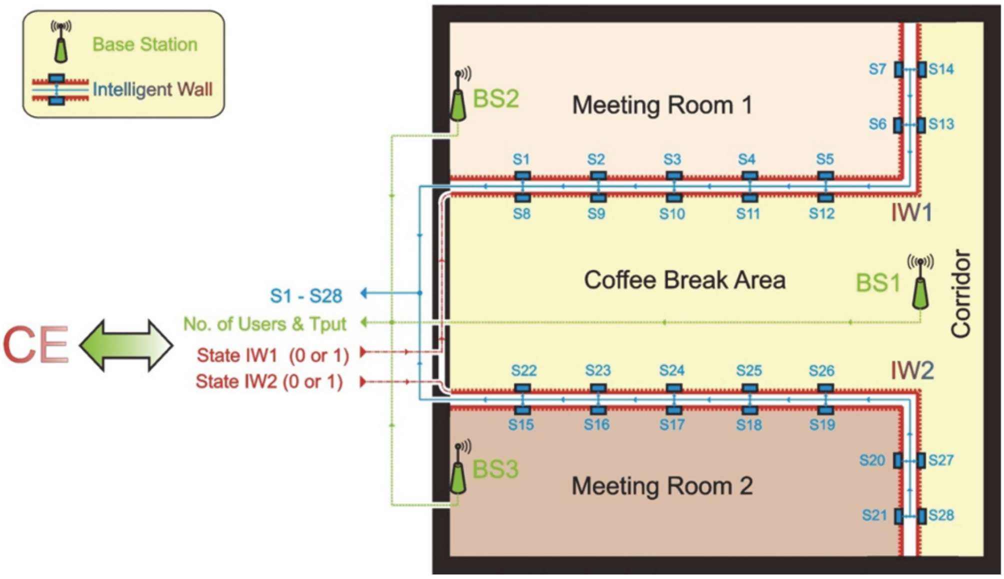

Fig. 5.1 The case scenario

5.2.3 Monte Carlo Snapshots

The entire system is simulated using the classic Monte Carlo snapshots approach [28]. We assumed several different distributions of active users corresponding to the different situations (modes) in the conference center as defined by probabilities (Tab. 5.2). Modes are numbered in a range between 1 and 4. The table contains the probabilities of the appearance of an active user in each part of the scenario - p_{R1} represents probability of being in the meeting room 1, p_{R2} in the meeting room 2 and p_{corr} in corridor & coffee break area. The overall number of active users is generated randomly in a range between 100 and 150. Mode No. 1 stands for the mode called "Distributed users", No. 2 "Users in both meeting rooms", No. 3 "Coffee break" and No. 4 "Users in meeting room 1".

No.	p_{R1}	p_{r2}	p_{Corr}	name
1	0.30	0.30	0.40	Distributed users
2	0.45	0.45	0.10	Users in both MRs
3	0.01	0.01	0.98	Coffee break
4	0.90	0.00	0.10	Users in MR1

Tab. 5.2 Active users space distribution modes

5.3 Simulation Results

5.3.1 Simulations of Different Modes

To examine the influence of the Intelligent Walls on the system, the aforementioned modes were simulated and compared. Ten thousand Monte Carlo snapshots for each of the 4 modes were simulated and the results were averaged in order to limit fluctuations caused by the users' positions. Based on the distribution of the users, the number of connected users and system throughput were calculated for all four IW states in each snapshot. As can be expected, the IWs in the ON states generally reduce the interferences, that is to say, increasing SINR and the overall throughput, while reducing the coverage in some parts of the scenario, meaning reducing the number of users which can be connected to the network.

In order to evaluate the influence of the Smart Environment on the overall system performance we defined a relative system performance measure which took into account both the number of users connected to the network and overall system throughput:

$$P_{sys} = \frac{w_U \cdot \frac{U_{XY}}{U_{00}} + w_T \cdot \frac{T_{XY}}{T_{00}}}{w_U + w_T}, \tag{5.3}$$

where P_{sys} represents the relative system performance [-], w_U weight of the relative number of active users [-], U_{XY} the number of users connected if configuration *XY* is active [-], U_{00} number of users connected if configuration *00* is active [-], w_T weight of relative system throughput [-], T_{XY} system throughput if conf. *XY* is active [bps] and T_{00} system throughput if conf. 00 is active [bps]. The value of the relative system performance is relative to the IW configuration 00 (both IW are switched off) which corresponds to the situation when no IW is installed.

The simulation results for all 40 thousand snapshots are in Fig. 5.2 for relative system performance. All of them are separated by the four modes according to Table 5.2. For each mode, the relative system performance is given for the four configurations of IWs. The best configuration can be identified for each mode. The results show that by properly controlling the IWs, it can bring benefits in the form of higher system performance. On the other hand, any improper way of controlling can cause degradation of the system parameters. Data from the sensors, together with the best configuration chosen, were recorded and used as input data for machine learning.

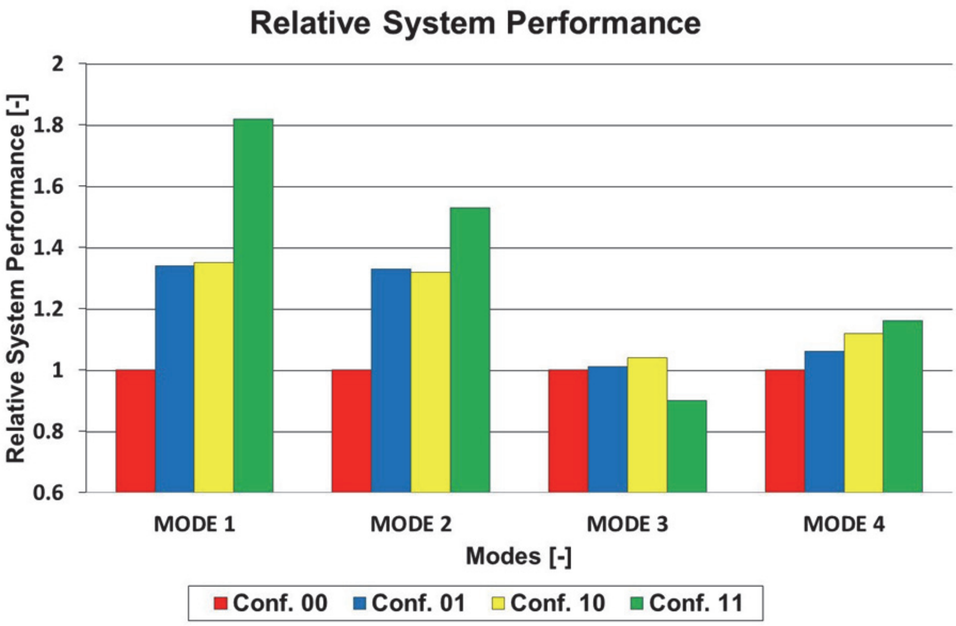

Fig. 5.2 Simulated relative system performance for all modes and configurations

5.3.2 Decision Making and Learning

The CE of IWs should be able to choose the best configuration of the IWs according to the results in Fig. 5.2. To do this autonomously, the mode of the active users' distribution must be identified first. The inputs from suitably distributed sensors should provide sufficient information. Then the best IW configuration must be selected, either using a static decision process, or, as we propose, based on a machine learning algorithm utilizing the system performance history. Simulation results, together with the data from the sensors recorded for each snapshot, were used as the input data for the machine learning.

As stated earlier, one of the main properties of our IW system implementation is the ability to learn. In our test scenario it means that the CE learns which IW configuration is the best for the actual situation as described by the sensors and the system performance. The Artificial Neural Network (ANN) [29] was chosen as a suitable instrument to solve this task.

After the deployment of IWs the CE should start to observe and collect the data to learn. Once the CE has learnt, it starts to make decisions and control the IWs – the Smart Environment. Performance increases as further input data for the learning process are available. To verify the process, the following simulations were performed. Firstly, the system observes and subsequently learns. Let us consider that the system randomly switches configurations of IWs and collects corresponding information on the resulting system performance (5.3) and sensors inputs; in fact it gradually builds the snapshot database. Of course, each random change of the IW configuration can degrade the actual system performance temporarily so that the learning phase, especially the timing, would have to be carefully implemented in real world conditions. However, our simulation proved that the learning process can be quite fast in terms of the size of the learning dataset.

Fig. 5.3 shows the relative system performance as a function of a number of snapshots used for the learning process using our ANN implementation. The process was simulated using ten thousand Monte Carlo Snapshots, but only a small percentage of these snapshots were used for the CE to learn. After the learning phase, it starts to control the IW configuration autonomously using the ANN and the inputs from the sensors only. To simulate such behavior, the remaining data (snapshots), which were not used for learning, were used as input for the testing of the CE functionality.

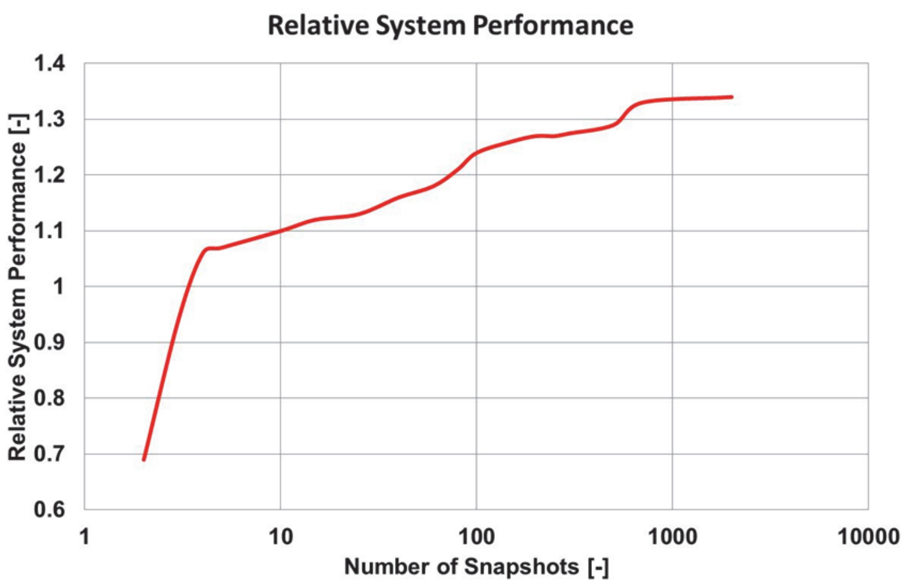

Fig. 5.3 Relative system performance vs. number of snapshots used for learning

If the learning algorithm is implemented as a continuous process, the Smart Environment with the IWs is able to adapt to any environment, and therefore can be deployed in any environment without any specific settings. Even if the floor inside the building is rebuilt or reconstructed, or the scenario geometry is changed significantly, the CE is able to adapt to the new conditions.

6 Conclusion

The thesis presents a new approach to controlling indoor propagation environments. Unlike other approaches, the concept is based on the idea of Intelligent Walls, i.e. common existing walls equipped with active FSS and sensors which are a part of the cognitive wireless system driven by a cognitive engine. It was proved that a system of frequency selective walls can have a significant influence on the signal coverage and can influence the shape of signal coverage according to one's requirements.

Further investigations showed that the proposed Intelligent Walls, when connected to the wireless cognitive system utilizing algorithms of the artificial intelligence, can increase system performance. The Intelligent Walls, acting as cognitive nodes, observe the environment (position of users) and transfer information to the cognitive engine which uses the information, together with information from Base Stations, for learning, optimization and deciding.

System level simulations of the wireless cognitive network in the simple indoor scenario proved that control of the propagation environment can increase system performance up to 80%. Although our results are based on simulations, a positive influence of Intelligent Walls can be expected.

The simulations were performed using a new 3D deterministic model which was originally designed for electromagnetic wave propagation predictions in subterranean galleries and tunnels and later developed for purposes of propagation predictions in indoor Smart Environments. The model provides fast site-specific predictions of both narrowband and wideband channel parameters while avoiding the use of material properties such as permittivity and permeability. These properties are replaced by a small number of probabilistic parameters used in solving ray/obstacle interactions (reflection, absorption, diffuse scattering) and can be tuned on the basis of measured data.

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List of Candidate's Works Relating to the Doctoral Thesis

Articles in Impacted Journals

[1] L. Subrt and P. Pechac, "Semi-Deterministic Propagation Model for Subterranean Galleries and Tunnels," IEEE Transactions on Antennas and Propagation, vol. 58, pp. 3701-3706, 2010. (50%)

[2] L. Subrt and P. Pechac, "Intelligent Walls as Autonomous Parts of Smart Indoor Environments," IET Communications, Accepted May, 2011. (50%)

[3] L. Subrt, D. Grace and P. Pechac, "Controlling the Short-Range Propagation Environment Using Active Frequency Selective Surfaces," Radioengineering. 2010, vol. 19, no. 4, p. 610-615, 2010. (33%)

[4] L. Subrt and P. Pechac, "Advanced 3D Indoor Propagation Model: Calibration and Implementation," EURASIP Journal on Wireless Communications and Networking, accepted October, 2011. (50%)

Publications Listed in Web of Science

[5] L. Subrt and P. Pechac, "A 3D model for wideband propagation predictions in tunnels," in 3rd European Conference on Antennas and Propagation, 2009. EuCAP 2009. , 2009, pp. 2253-2256. (50%)

[6] L. Subrt and P. Pechac, "The Influence of Dynamic Changes of Indoor Scenarios on Electromagnetic Wave Propagation," in 4th European Conference on Antennas and Propagation, 2010. EuCAP 2010., 2010, pp. 2253-2256. (50%)

[7] L. Subrt and P. Pechac, "Influence of modelling diffraction on electromagnetic wave propagation predictions in subterranean galleries," in Proceedings of the 5th European Conference on Antennas and Propagation (EUCAP), 2011, pp. 1651-1654. (50%)

Other Publications

Publications Listed in Web of Science

[8] L. Subrt, P. Pechac and S. Zvanovec, "New Approach to Modeling of Diffuse Reflection and Scattering for Millimeter-wave Systems in Indoor Scenarios," in Proceedings of PIERS 2010 in Cambridge [CD-ROM]. Cambridge, MA: The Electromagnetics Academy, 2010, p. 1068-1071. ISBN 978-1-934142-14-1. (33%)

Anotace

Dizertační práce se zabývá problematikou inteligentního řízení interiérů budov z hlediska šíření elektromagnetických vln. Nejprve je čtenář seznámen se základy ideálního (Mitolova) kognitivního rádia, dále jsou stručně zmíněna tzv. chytrá prostředí stejně jako základy detekce pohybu uživatelů uvnitř budov, včetně jeho modelování a predikce. Podobným způsobem jsou v práci obsaženy i základní informace o modelech pro šíření vln ve vnitřních scénářích. Výše zmíněné poznatky jsou uvedeny pouze v rozsahu potřebném pro další řešení cílů práce. Podrobné informace je možné nalézt v uvedené literatuře.

Na základě cílů dizertační práce byl navržen nový 3D semi-deterministický model pro šíření vln založený na paprskové optice a stochastickém přístupu. Jeho hlavními výhodami jsou především jednoduchý popis materiálových vlastností překážek (stěn), a to za pomoci trojice pravděpodobnostních parametrů. Model se dále vyznačuje rychlým výpočtem interakcí mezi paprsky a překážkami a také tím, že je schopen uvažovat všechny důležité fyzikální jevy (odraz, průchod, absorpci, difrakci a difúzní rozptyl), bez znalosti materiálových konstant (permitivita a permeabilita). Další neméně podstatnou vlastností modelu je i schopnost predikovat nejen signálové pokrytí, ale i širokopásmové parametry kanálu (impulzní odezvu a úhly příchodů paprsků). Správná funkce modelu je ověřena na testovacích scénářích, kde jsou výsledky výpočtu pokrytí porovnávány s naměřenými daty. Rozdíly mezi simulací a měřením jsou kvantifikovány a jsou uvedeny i jejich pravděpodobné příčiny. Model je nasazen jako základní výpočetní nástroj pro predikci signálového pokrytí, které je dále využíváno systémovým simulátorem inteligentní bezdrátové sítě.

Inteligentní bezdrátová síť v této práci je uvažována jako systém uvnitř budovy používající jako základního stavebního kamene tzv. inteligentních stěn, tj. běžných stěn doplněných o aktivní frekvenčně selektivní povrch a sensory. Aktivní frekvenčně selektivní povrch umožňuje měnit elektromagnetické vlastnosti stěny na základě aktuálních podmínek, které jsou dány umístěním a požadavky uživatelů ve scénáři. Právě poloha uživatelů je zjišťována za pomoci sensorů, které jsou součástí inteligentních stěn. Systém stěn je řízen na základě aktuálních požadavků uživatelů v síti za pomoci kognitivních principů tak, aby byl výkon celého systému v daný okamžik co možná největší.

Pomocí simulací bylo ukázáno, že inteligentní řízení prostředí umožňuje zvýšit výkon sítě až o 80% s využitím předcházející zkušenosti, získané pomocí inteligentních algoritmů učení, které jsou implementovány díky technice umělých neuronových síti.

Na závěr práce je provedeno zhodnocení splnění cílů práce a také definováno další směřování výzkumné činnosti v této oblasti.