System-Level Simulation and Radio Resource Management for Distributed Antenna Systems with Cognitive Radio and Multi-Cell Cooperation using Imperfect Information

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ABSTRACT: *The performance of cellular networks will experience a considerable improvement by the use of newtechnologies such as distributed antenna systems (DASs), multi-cell cooperation (MCC), and cognitive radio (CR).However, several issues remain open in the system-level evaluation, radio resource management (RRM), and particularlyin the design of billing/licensing schemes for these types of system. This paper proposes a system-level simulator(SLS) that will help us address these issues. An advanced RRM solution is also proposed for a multi-cell DAS in adense urban Manhattan scenario with two levels of cooperation: inside the cell (intra-cell) to coordinate the transmissionof distributed nodes controlled by the base station of the cell, and between cells of a cluster (inter-cell) toadapt cell transmissions according to updated inter-cell interference measurements. The RRM solution blends networkand financial metrics using the theory of multi-objective and financial portfolio optimization. In this paper each network/spectrum resource is considered as a financial asset whose allocation has to be optimized based on economic metrics such as return and risk (i.e., variation of the return). The core of the intra-cell RRM algorithm is based on an iterative weighted least squares (WLS) optimization scheme where power levels and beam-forming vectors are jointlydesigned to comply with a target instantaneous SINR (signal-to-interference-plus-noise ratio) threshold for each transmission.This instantaneous SINR threshold ensures the transmission of the selected modulation and coding scheme(MCS) with a given value of BLER (block error rate) and spectral efficiency. The WLS scheme allows for a smoothintegration of scheduling and adaptive modulation and coding (AMC) schemes with the underlying space division multiplexing(SDM) physical layer. Convergence speed is improved by reusing the outcome of previous WLS iterations.The weight coefficients of the WLS optimization contain network metrics such as queue length and fairness, as well aseconomic metrics such as return and risk. This process is complemented with a multi-objective and financial portfoliooptimization stage for joint spectrum selection and resource (chunk) allocation that attempts to maximize return and minimize risk. Cells within a cluster exchange the results of their optimization processes for purposes of rejectinginter-cell interference, thereby achieving MCC. All resource allocation schemes use an imperfect copy of channel and queueing state information, which is the result of inaccurate measurements, imperfect feedback, or sensing errors.*

Keywords: Distributed Antenna Systems (DASs), System-Level Simulation (SLS), Space Division Multiplexing (SDM), Radio Resource Management (RRM), Multi-objective and Financial Portfolio Optimization

1. Introduction

1.1 Background

Future wireless networks will require advanced schemes to cope more efficiently with harsh propagation conditions,higher levels of interference, and increasing bandwidth demands. Examples of these new schemes are distributed antenna systems (DASs), multi-cell cooperation (MCC), and cognitive radio (CR). Unlike conventional cellular systems, the antennas of a DAS are not co-located at the base station (BS). Instead, they are distributed within the cell, mimicking a macroscopic multiple-input multiple-output (MIMO) system with high diversity gains [1]. In DAS, the distributed nodes are interconnected, via a coaxial cable or optical fibre, to the BS at the centre of the cell. This BS hosts the main management and signal processing tasks of the entire cell (including the distributed nodes). A related approach is used in MCC systems (e.g., [2]). The BSs of different cells act themselves as distributed elements of the macroscopic MIMO system by exchanging information between them. The performance of MCC is thus limited by the accuracy of the exchanged information between BSs and their distributed coordination capabilities [2].

Despite their advantages, these new technologies will only support one portion of the predicted demand for connectivity.This implies the need for more spectrum bands. Since spectrum is a limited resource, major efforts are currently focused on more flexible and dynamic spectrum sharing and licensing schemes. This has paved the way for smart sensing and adaptation technology called cognitive radio (CR), which will allow unlicensed terminals to opportunistically access underutilized licensed bands [3]. Therefore, opportunistic spectrum access via CR and improved signal transmission/reception via DAS-MCC are expected to mitigate the bandwidth scarcity problem for future applications.

1.2 Open Issues and Previous works

Most of the literature related to these technologies has been focused on physical (PHY) layer and resource allocation aspects (see [1]-[3]). However, several other issues need to be addressed before new wireless technologies are finally commercialized. New technologies must be tested in an environment that closely matches a real network with tens/hundreds of BSs serving hundreds/thousands of terminals with different propagation and traffic conditions. This testing must be also accompanied by an efficient radio resource management (RRM) algorithm, where lower and upper (application) layers converge. Furthermore, since CR enables the opportunistic use of spectrum under the control of different operators with different licensing/billing agreements, the RRM must also consider economic/financial information.The ideal set-up for this system-level evaluation is an operational cellular network. However, risks of service disruption and compatibility issues avoid full testing in live networks. In addition, prototypes have the disadvantage of high costs and unrealistic deployments. Software-based system-level simulators (SLSs) avoid these issues and have therefore become a cornerstone in network design and optimization [4].

SLSs provide a virtual and flexible way to test new algorithms and collect system-level performance metrics (e.g.,cell throughput, end-to-end delay, spectrum efficiency, average revenue per terminal, call drop rate, etc.). Different approaches for SLS have been proposed in the literature. For example, a SLS of a time-division spread CDMA (TDSCDMA)system was presented in [5] using OPNET [6]. OPNET is a commercial software package whose tools are available to the consortium (now part of Riverbed systems). The focus of OPNET is mainly on upper layers. The work in [7] simulated a TD-SCDMA system using the open-source OMNeT++ platform. As an alternative to these simulators, an open simulator developed in the Aachen University called OpenWNS was presented in [8]. Systemlevel simulation of distributed broadband wireless systems based on radio-over-fibre (RoF) infrastructure has been presented in [9] for the FP7 European research project FUTON. Using this simulator, the work in [10] has presented a detailed study of round robin (RR) and maximum-carrier-to-interference (MCI) scheduling algorithms with single and multiple antenna selection for DAS under different values of traffic load and transmit power. Improving on this previous approach, a joint scheduling and power control scheme for DAS has been proposed in [11]. This solution assigns initially one terminal per node. This is followed by an iterative joint optimization of power and the set of scheduled terminals (user removal) in order to comply with a target signal-to-interference-plus-noise ratio (SINR) for each selected terminal. The extension to systems with different modulation and coding schemes (MCSs) was proposed in [12]. Capacity and fairness of DAS with joint scheduling and power control has been reported in [13], while the beam-forming version has been provided in [14] under the assumption of imperfect channel state information (CSI).Distributed linear pre-coding and terminal selection for MCC has been studied in [15].

1.3 Paper Contributions

This paper presents the design of a SLS for the evaluation of RRM algorithms for cellular systems enabled with DAS,MCC and CR. The RRM solution presented here is an improvement over previous works by including in its design financial information

and the assumption of imperfect network state information. This means that the SLS considers the economic aspects of different frequency bands controlled by different operators, which will be typical in future CR and self-organized networks. It also enables the option of different levels of accuracy of channel and queueing state information of the terminals. This allows us to mimic different types of decentralization and exchange of information,mainly inside the cell (intra-cell) and between cells (inter-cell). The latter one is used for purposes of multi-cell cooperation.

The paper focuses on the description of the simulator modules and the changes required to cope with the new transmission/financial design paradigm. The framework used in this paper is based on the theory of multi-objective and financial portfolio optimization, which is commonly used in the fields of economics and finance theory. In the proposed approach, each spectrum and radio resource is considered as a financial asset whose allocation will attempt to simultaneously maximize economic return and minimize risk or the variance of the return. This spectrum allocation scheme is complemented with an inner radio resource management algorithm (intra-cell) that is in charge of power control, terminal scheduling, space division multiplexing (SDM) and adaptive modulation and coding (AMC) of the underlying DAS system.

The joint power and beam-forming optimization problem is here reformulated as a weighted least squares (WLS) optimization problem. This differs from conventional approaches (e.g., [16]-[18]), where the problem is formulated as the minimization of the total power subject to the SINRs of the terminals to surpass the reception threshold corresponding to the selected MCS. The main issue with these schemes is that their integration with scheduling and adaptive modulation and coding (AMC) is not straightforward. By contrast, the WLS formulation presented in this paper provides a smooth transition. The proposed WLS formulation ensures convergence to a solution that minimizes an error objective function. If the value of this error function is not zero (which means that the SINR requirements cannot be achieved) then either the MCSs or the set of scheduled terminals are modified (i.e., reduction of MCS order or terminal removal) so that the objective function can be further minimized in subsequent WLS iterations. The results of each WLS iteration are reused for the next iteration to be further refined, thereby speeding up convergence of the algorithm. The weight coefficients of the WLS optimization contain network metrics such as queue length and fairness, as well as economic metrics such as return and risk. This iterative WLS process is repeated until the error function becomes zero or null, which means that the scheduled terminals can transmit with their selected MCSs. The proposed algorithm is implemented in a highly dense urban Manhattan scenario with two distributed antenna systems: one indoor and one outdoor. The two subsystems are allowed to opportunistically allocate resources for secondary transmissions on the frequency band licensed to the adjacent (primary) network. Cells are arranged in groups or clusters of cells for purposes of multi-cell cooperation. Therefore, cells within a cluster can communicate sequentially with each other. Once each cell within a cluster has allocated resources using the proposed intra-cell allocation algorithm, it then proceeds to communicate its optimized transmission settings to the other cells in the cluster. The remaining cells in the cluster recalculate the resource allocation algorithm based on the updated transmission settings and therefore on the updated estimation of inter-cell interference. This multi-cell cooperation process is repeated until allocation is nearly optimum inside the cluster. In order to calculate inter-cluster interference efficiently, the results of the power levels and beam-forming vectors calculated in previous simulation runs or iterations of the central cluster are reused in the outer-clusters, thereby mimicking more efficiently system-level behaviour while reducing simulation complexity. This means that for each simulation run, only one cluster is simulated in full detail. Simulation results are obtained for a scenario with different values of economic return and risk for primary and secondary transmissions. The results suggest that the parameter that controls the balance between return and risk objective functions also controls the interferencecreated by secondary transmissions towards primary terminals. Therefore, it is possible to find a value of such parameter that will control the interference in the system and that will also maximize throughput.

1.4 Paper Organization
This paper is organized as follows. Section 2 describes the architecture of the simulator Section 3 describes the deployment scenario and the propagation model. Section 4 describes the link-to-system-level interface (LSLI) model. Section 5 describes traffic models and the frame definition. Section 6 presents the RRM solution and Section 7 explains an example of simulation results. Finally, Section 8 presents the conclusions.

2 Architecture and Types of Simulation

2.1 Simulator Architecture and Simulation Process
The architecture of a SLS must closely follow the architecture of the network to be simulated. Each module of the SLS resembles an element of the network, containing a set of parameters that can be adjusted by the user of the simulator according to a particular scenario. The SLS presented in this paper is based on an object-oriented programming language. It is an evolution of

the MOTION tool developed for different European research projects (e.g., [9]). The logical modules of the SLS are shown in Figure. 1, where the licensing (billing) and spectrum portfolio modules are the main additions with respect to a conventional SLS. Other additions to the tool are, for example, the impairment models used for the simulation of CRs, and the distortion effects of the radio-over-fibre (RoF) links between BSs and distributed nodes. These impairments are translated into imperfect channel and queuing state information. Imperfect network state information, in turn, is translated into decision/allocation errors that affect the performance and quality of communication links. The proposed simulator explicitly includes the effects of imperfect network state information on the performance of the RRM solution to be simulated.

The typical system-level simulation process can be briefly described as follows: once terminals, BSs and distributed nodes have been placed within the virtual geographical space following the target scenario, the SINR experienced by each terminal in each radio resource is obtained according to the selected propagation model. This channel quality information is obtained for all targeted radio resources and frequency bands of the different operators. This PHY-layer metric calculation must also include the effects of other schemes such as power control, beam-forming, link adaptation, and signal processing. The RRM module decides which terminals will transmit in which resources based on the previously obtained SINR metrics, traffic requests, and also based on the licensing/billing options of the spectrum portfolio. All resources are arranged according to a frame definition specific of the radio access technology (RAT) under consideration. The SINR quality metrics of the terminal over their allocated radio resources are typically mapped into a look-up-table (LUT) that describes the performance of the link- and PHY-layers in terms of block- or packeterror rate (BLER and PER, respectively). The process is repeated a number of iterations and a number of simulation runs (each run consists of a number of iterations) to collect statistically meaningful metrics.

The first step of the simulation process is the selection of the deployment scenario, which defines how the network elements are spatially placed, the type of antennas used, terminal density, mobility models, and the available frequency bands of different operators (via opportunistic CR). The scenario also determines the channel model to be used, which can be subdivided into fast fading, multi-path fading, path-loss, and shadowing or slow-fading models. The propagation model describes how the wireless medium behaves in time, space and frequency. The simulator must also consider the dynamics of the data generation process for each terminal or type of terminal using a convenient traffic model. The traffic model refers to how often data streams arrive to the system, thereby reflecting the behaviour of application layers. Another crucial part of the SLS is the interface with link-layer results. Typically, once a channel instance of a particular terminal has been obtained, its effective SINR is mapped into the LUT that contains link-layer metrics. At the core of the SLS, we find the RRM algorithm. Based on traffic requests and the available channel state information, the RRM module allocates resources to the terminals. All network information available at the RRM module will be considered to be inaccurate, reflecting the imperfect nature of the process of acquisition, estimation and transport of the relevant information about the network (channel and queuing states). This imperfect information framework is particularly useful for cognitive radio systems, where sensing of opportunities is subject to impairments that directly translate into conflicts and interference to primary transmissions. In MCC, this RRM process is repeated in an iterative manner for all the cells in the cluster. The interference measurements updated from each cell are used to refine the allocation decisions of the other cells within the cluster.

2.2 Simulation Modes
The simulator is a piece of software that is enabled with several modes of operation that allow the user of the tool to perform different types of simulation that involve a different use of the computational resources with different degrees of simulation accuracy.

2.2.1 Dynamic Mode
In fully dynamic mode (FDM), full mobility is enabled: terminals travel in the network experiencing handover between cells and clusters of cells. Path-loss, shadowing and fast-fading propagation components are re-computed every transmission time interval (TTI). The new position of each terminal in the next TTI is computed according to a mobility model.

2.2.2 Combined Snapshot Mode
In combined snapshot-dynamic mode (CSM), terminal mobility and handover processes are disabled. A given number of simulation runs are performed. Path-loss and shadowing values are computed at the beginning of each simulation run and remain constant until the end of the run. Fast fading is re-computed every TTI. This mode increases simulation speed as different runs (snapshots) can be performed in parallel. Two types of cluster configuration are defined: central and non-central cluster mode. In the central-cluster approach, terminals are placed in the coverage area of a central group of BSs and statistics are collected only for the cluster of these BSs. The surrounding clusters are assumed to be fully loaded, and contributing to

interference only. In the non-central approach all clusters are included in the simulation process. In this paper we use a hybrid mode, where the surrounding clusters reuse the transmission settings of the central cluster obtained in previous simulation runs. This hybrid mode mimics real inter-cluster interference without the need of simulating the entire set of clusters, which considerably reduces simulation time and complexity.

3. Deployment Scenario and Propagation Models

The dense urban Manhattan network scenario has been selected here as the main target of the SLS. It consists of a rectangular grid of distributed nodes and BSs. The grid follows the regular structure of a city with buildings, streets, and blocks, all assumed to be of similar size. For simplicity, the nodes are considered to be located at convenient positions on the street crossings (see Fig. 2). Therefore, the Manhattan deployment can be defined by three parameters: the node street spacing (z), and both the street and building widths (denoted, respectively by w and v). The top part of Figure. 2 shows a cell in the Manhattan deployment with $L = 9$ distributed nodes. Note that cells have a square shape for simplicity in the given scenario. The node at the center of the cell acts as the control unit (base station) for all the other nodes. Nodes are assumed to be attached to this control unit via cables or optical fibre. Terminals are placed along the streets of the deployment either in LOS (line-of-sight) or NLOS (non-line-of-sight) with respect to each node. The figure also shows indoor radiation nodes, which are assumed to operate in an adjacent frequency band that can be opportunistically accessed by means of CR. A wall penetration loss of 8dB will be considered in all simulations. In Figure. 2 the superimposed squares show the virtual limits of each cell. A multi-cell arrangement of $Q = 9$ clusters of cells is also shown at the bottom of Figure. 2. The arrows indicate the information flow between cells inside a cluster for purposes of multi-cell cooperation.
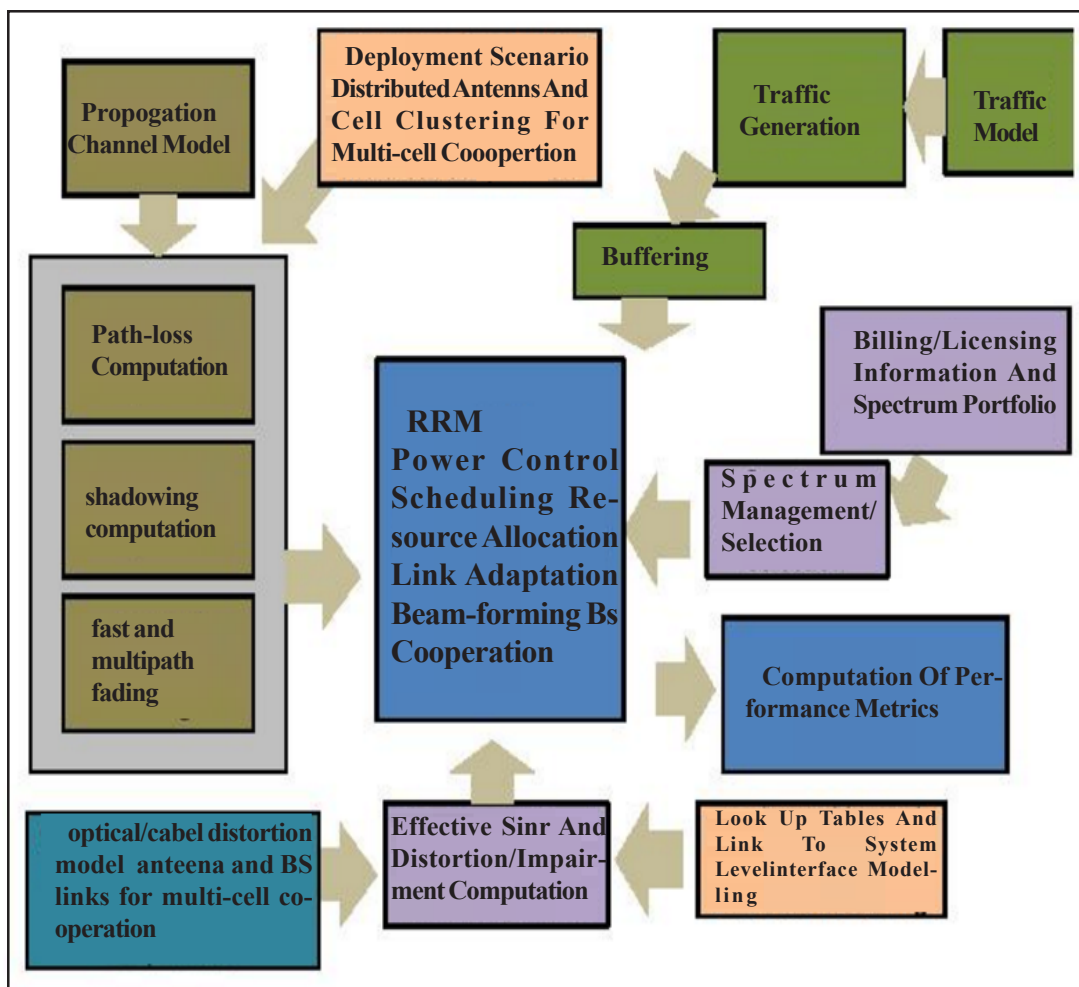

Figure 1. Architecture of the system-level simulator (SLS)

Since the deployment scenario defines the space configuration where electromagnetic waves will propagate, it also leads to the definition of the propagation model. The propagation model is divided into four distinct components: path-loss, slow fading (shadowing), multi-path and fast fading. The reduction of radio signal strength impinging on the receiver antennas is a result of their combined effects. Path-loss is the attenuation that a signal suffers as the result of the initial radiation power being distributed over larger surfaces as the waves propagate. In free space, energy is distributed over concentric spheres which leads to the path-loss exponent of 2. More complex propagation settings experience higher path-loss exponents, which is typical of dense urban scenarios. Fast fading is the result of multiple copies of the signal travelling across different paths in the network and being superimposed in a destructive manner at the receiver within the duration of a symbol. The result of fast fading is a randomly distributed channel envelope. The most common fast fading model considers uniformly distributed scatterers that contribute with a set of randomly delayed copies of the signal. This is the very well known Rayleigh channel distribution. Other commonly used channel distributions include Rice and Nakagami, which are useful for describing different sets of propagation conditions. Multi-path fading is also a destructive superimposition of the copies of a signal travelling through different paths. However this superimposition occurs across different symbols, thus causing inter-symbol interference (ISI). ISI is usually removed by a convenient equalization technique or by means of orthogonal frequency division multiplexing (OFDM). Shadowing is the effect of objects that "*shadow*" some regions from correct signal reception. It is also know as slow fading mainly because it occurs over long periods of time (mainly as a deviation of the path-loss component). The simulation results presented in this paper use the B1 WINNER model [19], which is suitable for the modelling of a typical urban micro-cell environment with antennas near the street level, terminals both in LOS and NLOS with speeds in the range of 0-70 km/hr, and with an operational frequency in the range of 2-6 GHz. The parameters for modelling the multi-path and fast fading components are given in [19] for terminals in LOS and NLOS. Fast fading is modelled using a modified implementation of the Jakes model: the sum of sinusoids (SoS). The method of SoS is a good approximation for the modelling of Rayleigh fading considering randomly and uniformly spaced scatterers [20]. The shadowing model, which is assumed log-normal distributed, makes use of a bi-dimensional SoS with spatial correlation [20]. This paper considers several antennas per distributed node and only one antenna per terminal. The antennas at the distributed nodes are used for beam-forming and space division multiplexing. The stochastic MIMO channel model defined by the WINNER documents (see [19]) has been used for implementation in the SLS. The radiation pattern of each antenna can also be configured by the user of the simulator.
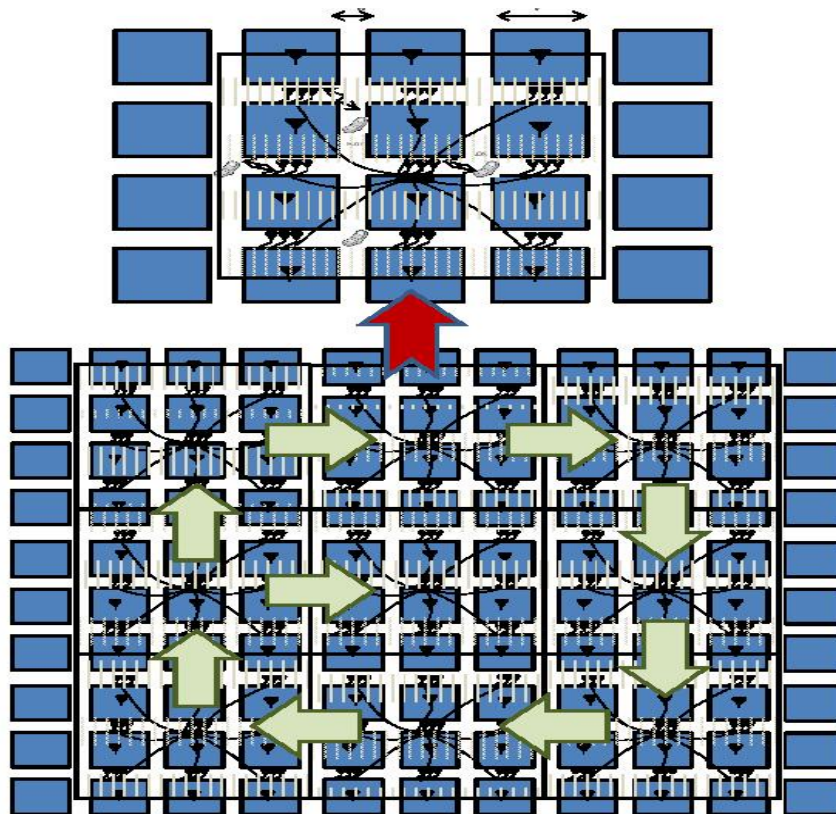

Figure 2. Manhattan deployment scenario (single and multi-cell configurations).

4. Link-to-System Level Interface (LSLI) modeling

A critical issue in SLS design is the methodology adopted to recreate the different processes of the network. Since some of those processes occur at different time-scales, they cannot be included in the same simulation loop, mainly because this would lead to extremely long simulation times. The simulation of an entire cellular system cannot include PHY layer details at the bit or symbol level. Instead, the simulation process is split into two stages. An off-line link-layer simulation tool that addresses processes in short time scales, (at the symbol and bit level), is commonly employed. The results of these link-layer simulations are imported into the main SLS using LUTs or other mathematical abstraction models. The link-layer simulator uses a granularity at the bit and symbol level, whereas the SLS uses a granularity at the radio-resource (chunk) and block levels. The accuracy of the interfacing compression methodology between link layer and the SLS is thus crucial for the validity of the simulation. Therefore, a compression model that encapsulates the PHY-layer in the most accurate way with the minimum possible complexity (to reduce simulation time)must be proposed. The typical process consists of two basic steps: 1) Obtain the instantaneous or effective SINR experienced by the terminal over the target radio resources, and 2) Map this value into a LUT that describes BLER or PER in terms of the effective SINR. The term effective SINR is used to describe a mathematical function that is helpful to compress the information of channel states of a block of sub-carriers. The effective SINR can be conveniently mapped to a representative metric suitable for the SLS, such as packet or block error rate. The collected BLER or PER metrics for all the terminals can be then used to calculate system-level metrics. The LUTs are obtained via off-line PHY-layer simulation.

Let us now introduce a more formal representation of these mapping processes and interfacing models. We use the methodology described in [21] for the WINNER project, where the authors propose a generic link performance model that captures the performance of both the link layer and the mapping/compression processes. The proposed link performance model can be divided into three sub-models or entities, as shown in Fig. 3. The first entity is in charge of extracting quality measures from all of the parameters involved in the simulation. The quality measures are the metrics that represent in the best way the state of the network (e.g., the SINR values experienced by the terminals across different resources). The extracted quality measures are then passed to a compression stage which is used to reduce the complexity of mapping operations. The compression stage then produces a reduced number of metrics that can be mapped to a link-layer metric of interest, mainly PER or BLER, by using a LUT or mapping function. The compression stage is mainly used in multi-carrier systems to obtain a single performance metric that captures the performance of a block of sub-carriers, each one with potentially different SINR values. The main challenge, therefore, is to find the appropriate quality measures, the best compression rule and the optimum mapping function. Conventionally, the more appropriate quality measure is post-processing or post-detection SINR values, which can be defined as the SINR experienced at the end of the receiver processing operation [22]. Several compression techniques have been proposed in the literature. In this paper, we use the exponential effective SINR compression method (EESM) with AWGN(additive white Gaussian noise) fixed mapping functions. The MCSs to be used correspond to the convolutional turbo coding scheme used in WiMAX [23]. The LUTs to be used for a block of 7200 sub-carriers for different modulation and coding schemes are given in [23], all calculated over AWGN channels. The optimum parameters for EESM are also given in [23].
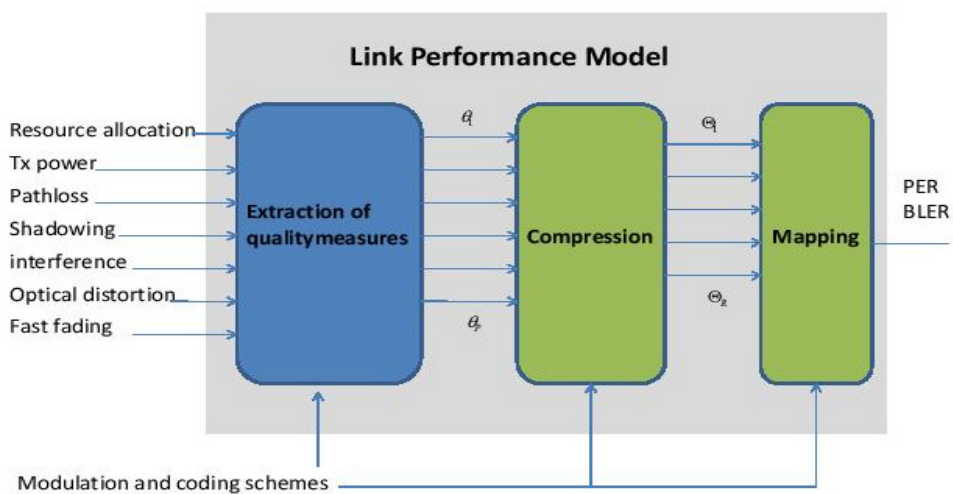

Figure 3. Link-to-system level interface model .

The LSLI model can also consider the impairments of the network to be simulated. In our case, the impairments that need to be added in the simulator are the imperfect sensing features of CRs, which are translated in imperfect channel and queueing state information, the limited communication bandwidth between BSs when using multi-cell cooperation, and the distortion effects of the links between the distributed nodes and the central BS of each cell when using RoF links. These impairments are included in the entity dedicated to the extraction of the quality measures in Figure. 3.

5. Traffic Models and OFDMA Frame Definition

5.1 Traffic Models
The SLS supports two types of traffic: full queue, in which all buffers are assumed to have information to be transmitted, and the option with random arrivals, in which different packet arrival and service distributions can be implemented. Service distributions for voice-over-IP (VoIP), file transfer protocol (FTP) calls, web browsing sessions, and non-real- time video (NRTV) calls have been included in the simulator. Advanced terminal mobility models based on Markov chains and random changes in direction and speed have also been included. The option of full queue is commonly used to study the capacity limits of wireless transmission systems. It thus provide an idea of the boundaries and upper limits under full traffic conditions. Therefore, it is useful to decouple the effects of application layers from the lower layers of the transmission systems.

5.2 OFDMA Frame Definition
The SLS supports a generic OFDMA (orthogonal frequency division multiple access) frame for resource allocation. OFDMA and its variations (e.g. single carrier frequency division multiple access or SCFDMA), have been selected by several standardization bodies for beyond 3G networks (such as LTE -long term evolution- and WiMAX -worldwide interoperability for microwave access-). OFDMA inherits the virtues of OFDM modulation technology in terms of its ability to transform a wideband frequency selective channel into a set of parallel narrowband flat-fading subchannels, thereby reducing complexity of the equalization stage at the receiver. Furthermore, OFDMA implements a hybrid multiple access technique that combines the benefits of frequency (FDMA) and time division multiple access (TDMA). The SLS presented here uses a generic OFDMA frame with N_s OFDM symbols and N_f sub-carriers. A basic radio resource unit or chunk to be used by the radio resource manager consists of a rectangular array of N_{fr} sub-carriers and N_{sr} OFDM symbols, as shown at the top of Figure. 4. The frame definition in Figure. 4 also considers a scenario with multiple cells (horizontal axis), multiple distributed nodes (axis perpendicular to the plane of view) and multiple frequency bands of multiple operators with different licensing/billing schemes (vertical axis). Some of these frequency bands are licensed to the terminals being managed and others will be accessed in an opportunistic fashion. It is the task of the RRM to decide which transmissions are allowed in the licensed frequency band and which transmissions can be directed to the unlicensed frequency without perturbing the performance of the primary terminals in the adjacent band, which in our case are the indoor terminals in Figure 2. The modulation parameters used in the simulator correspond to those of the WiMAX standard for a 10-MHz bandwidth using 1024 sub-carriers with 720 for data transmission and frame duration equal to $F_l = 5ms$ [23].

6. Radio Resource Management (RRM)

6.1 Signal Model
Each transmission in the network can use one of the M possible modulation and coding schemes (MCSs), which are arranged in increasing order according to their SINR requirements, denoted here by $\gamma^{(m)}$. This means that $\gamma^{(m)} > \gamma^{(m-1)}$, $\forall m \in \{1,...,M\}$. A set of K potential terminals is randomly deployed in the cell every time-slot. The channel between user k and the lth node of the ith cell in the pth sub-carrier of the dth frequency band of the qth cluster will be given by

$$\boldsymbol{h}_{l,i,k}^{(p,q,d)} = [\, h_{l,i,k}^{(p,q,d)}(0)\,,\,...\,,\,h_{l,i,k}^{(p,q,d)}(N-1)\,]^T,$$

where $(.)^T$ is the vector transpose operator and N is the number of co-located antennas per distributed node. Each node l in cell i will use a beam-forming vector denoted by:

$$\mathrm{w}_{l,i,k}^{(p,q,d)} = [\, w_{l,i,k}^{(p,q,d)}(0)\,,\,...\,,\,w_{l,i,k}^{(p,q,d)}(N-1)\,]^T.$$

The channels of different terminals and different distributed nodes are obtained according to the selected propagation model defined in subsection 3. The signal transmitted by the lth node of the ith cell will be denoted by

$$s_{l,i,k}^{(p,q,d)} = [\, s_{l,i,k}^{(p,q,d)}(0), \dots, s_{l,i,k}^{(p,q,d)}(S-1)\,]^T,$$

where S is the number of symbols. The symbols have unitary power: $E = [(\, s_{l,i,k}^{(p,q,d)}\,)H_{s_{l,i,k}^{(p,q,d)}}\,] = 1$, where $E\,[.]$ is the statistical

expectation operator and $(.)^H$ is the hermitian vector transpose operator. The transmit power of node l in cell i of cluster q towards terminal k is denoted by $P_{l,i,k}^{(p,q,d)}$. The signal received by terminal k can be mathematically written as follows:

$$\mathbf{y}_k^{(p,d)} = \sum_{q=1}^{Q} \sum_{i=0}^{I} \sum_{u \in \mathcal{S}_{i,q}} \sum_{l=1}^{L} \sqrt{P_{l,i,u}^{(p,q,d)}} (\mathbf{w}_{l,i,u}^{(p,q,d)})^H \mathbf{h}_{l,i,k}^{(p,q,d)} \mathbf{s}_{l,i,u}^{(p,q,d)} + \mathbf{v}_k^{(p,d)} \tag{1}$$
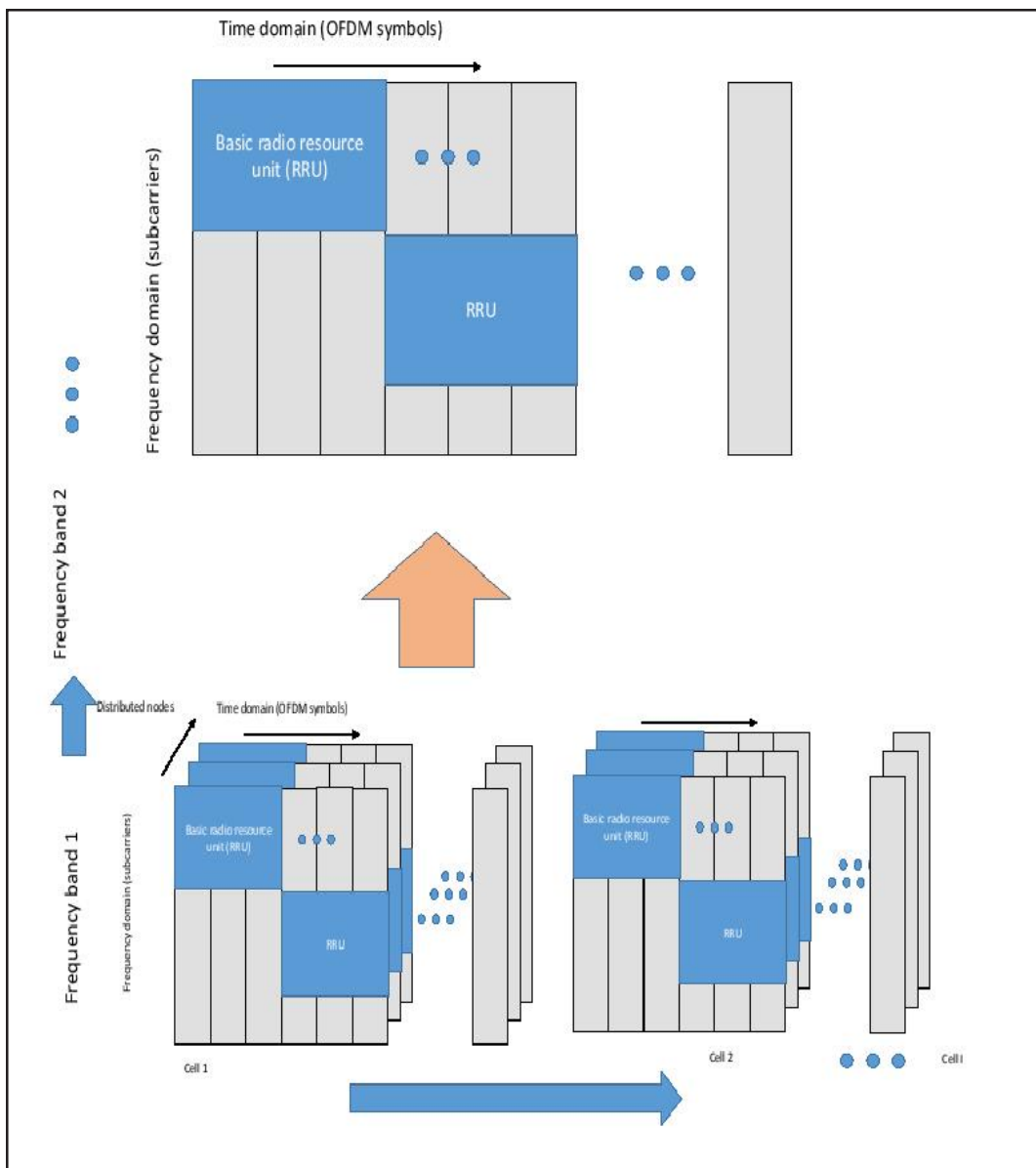

Figure 4. Frame for radio resource allocation.

where $S_{i,q}$ is the set of users in the coverage area of cell i in cluster q, and $\mathbf{v}_k^{(p,d)} = [\upsilon_k^{(p,d)}(0), \dots, \upsilon_k^{(p,d)}(S-1)]^T$ is the additive Gaussian noise with zero mean and variance σ_υ^2. Therefore, the SINR experienced by user k in cell i is denoted by $\Gamma_k^{(p,q,d)}$ and can be written as:

$$\gamma_{i,k}^{(p,q,d)} = \frac{\left| \sum_{l=1}^{L} \sqrt{P_{l,i,k}^{(p,q,d)}} (\mathbf{w}_{l,i,k}^{(p,q,d)})^H \mathbf{h}_{l,i,k}^{(p,q,d)} \right|^2}{\sigma_v^2 + \nu_{i,k}^{(p,q,d)} + \xi_{i,k}^{(p,d)}}, \qquad k \in \mathcal{S}_{i,q} \tag{2}$$

where

$$\nu_{i,k}^{(p,q,d)} = \left| \sum_{u \in \mathcal{S}_{i,q}; u \neq k} \sum_{l=1}^{L} \sqrt{P_{l,i,u}^{(p,q,d)}} (\mathbf{w}_{l,i,u}^{(p,q,d)})^H \mathbf{h}_{l,i,k}^{(p,q,d)} \right| \tag{3}$$

is the intra-cell interference for user k in cell i,

$$\xi_{i,k}^{(p,d)} = \left| \sum_{q=1}^{Q} \sum_{t=0; t \neq i}^{I} \sum_{u \in \mathcal{S}_{t,q}} \sum_{l=1}^{L} \sqrt{P_{l,i,u}^{(p,q,d)}} (\mathbf{w}_{l,t,u}^{(p,q,d)})^H \mathbf{h}_{l,t,k}^{(p,q,d)} \right| \tag{4}$$

is the inter-cell interference for user k in cell i. Due to imperfections in measurements, feedback, and estimation processes, the CSI available at the RRM will contain errors or deviations from the real instantaneous value. The estimated CSI will be denoted here by $\hat{\gamma}_{l,k}^{(p,q,d)}$. Frequency bands will be organized in blocks of radio resource or chunks. Each radio resource r will be allocated with a set of frequency bands denoted by S_r. The equivalent SINR for the block of sub-carriers S_r will be obtained using the exponential effective SINR formula:

$$\hat{\Gamma}_{i,k}^{(r,q,f)} = -\beta_{eesm} \ln \left(\frac{1}{|\mathcal{S}_r|} \sum_{p \in \mathcal{S}_r} e^{\frac{\hat{\gamma}_{i,k}^{(p,q,f)}}{\beta_{eesm}}} \right), \tag{5}$$

where β_{eesm} is the optimization parameter of a given modulation and coding scheme and which in this paper will be given by the values provided in [23] for the WiMAX standard. Once a user has been allocated to a given radio resource with a given modulation and coding scheme, and its EESM SINR has been otained, it is possible to calculate the block error rate (BLER) of the transmission by means of interpolation based on the values of a look-up table (LUT). The modulation and coding schemes to be used correspond to the WiMAX system as given in [23] with a block size of $S = 7200$ symbols over AWGN (additive white Gaussian noise) channels. Different values of BLER for the LUT can be calculated for different values of block size S by using the transformation $BLER = 1 | - | (1 | - |SER)^S$, where SER is the symbol error rate. Therefore, the $BLER$ can be calculated as follows:

$$B\hat{L}ER_{i,k}^{(r,q,f)} = f_{LUT} \left(\hat{\Gamma}_{i,k}^{(r,q,f)} \right), \tag{6}$$

where f_{LUT} is the mapping function of the look-up-table. Once the BLER has been obtained with this expression, then the instantaneous throughput of user k over the mth resource of frequency band f is given by:

$$T_{i,k}^{(r,q,f)} = \frac{(1 - BLER_{i,k}^{(r,q,f)}) B \cdot S \cdot R_c}{R_p \cdot F_l}, \tag{7}$$

where R_c is the rate of the turbo code scheme, B is the number of bits per constellation, F_l = 5ms is the frame-length, and R_p = 6 is the repetition coding rate [23].

6.2 Algorithm Description and Optimization

The objective of the proposed algorithm is to exploit both network and economic performance indicators so as to achieve a joint frequency selection and radio resource management. The algorithm is inspired by the theory of portfolio optimization commonly used in the field of economics, where a set of financial assets is selected so as to maximize the economic return and minimize the risk or variance of return. We assume that each frequency band d is a financial asset whose allocation we want to optimize so as to maximize return or profit and minimize the risk. Let us denote the instantaneous return per bit/sec/Hz of transmitted information in frequency band d as η_d . The instantaneous return of a transmission of user k over the rth radio resource of frequency band d can be written as:

Instantaneous return per user $= \theta_{i,k}^{(r,q,d)} = \eta_d \delta_{i,k}^{(r,q,d)}$

and the average return per user can thus be written as

Average Return per user $= E[\theta_{i,k}^{(r,q,d)}] = \bar{\theta}_{i,k}^{(r,q,d)} = \bar{\eta}_f T_{i,k}^{(r,q,d)}$,

The average risk or variance of the return is given by :

Risk per user $= E[(\theta_{i,k}^{(r,q,d)} - \bar{\theta}_{i,k}^{(r,q,d)})^2] = E[(\theta_{i,k}^{(r,q,d)})^2] - (\bar{\theta}_{i,k}^{(r,q,d)})^2 = E[\eta_f^2]E[(T_{i,k}^{(r,q,d)})^2] - \bar{\eta}_f^2(\bar{T}_{i,k}^{(r,q,d)})^2.$

It is worth pointing out that in the previous expressions the term $E[\eta_d^2] - \bar{\eta}^2$ is usually associated, in the context of financial portfolio optimization, with the financial fluctuations of the return/prices/licences of the assets under investigation, mainly because of changing market conditions. By contrast, the term $E[T_{i,k}^{(r,q,d)^2}] - (\bar{T}_{i,k}^{(r,q,d)})^2$ is associated with the fluctuations of the radio conditions in the network. Now, both types of fluctuations usually occur in different time-scales. Since we are interested in short-term fluctuations, particularly in the time-scale of radio resource allocation schemes, it would be possible to ignore the term related to financial fluctuations. However, in this paper these terms will not be dropped as they will be used for another purpose: they will be used for explicitly assigning different priority levels to primary and/or secondary transmissions, and thus allowing us to control in a better manner the proposed short-term radio resource allocation schemes. The variance of the throughput, given by $E[T_{i,k}^{(r,q,d)^2}] - (\bar{T}_{i,k}^{(r,q,d)})^2$ in cognitive radio systems is related to the risk of allocating secondary user transmissions that can potentially harm the performance of primary users, and it can be calculated on-line during the simulation process. Let us now consider that each resource r in frequency band d is allocated to a set of users denoted by $\mathcal{U}_{r,d}$ The set of allocated resources for frequency band d will be denoted by R_d By further considering the stacking of resources and allocated users as $R = \{R_1, ..., R_D\}$ and $U_R = \{U_{R1}, ..., U_{RK}\}$, respectively, the total instantaneous return and total average return over all resources of all the networks can be written, respectively, as follows:

$$\textbf{Total Instantaneous Return} = F(\mathcal{R},\mathcal{U}_\mathcal{R}) = \sum_d \sum_{r\in\mathcal{R}_d} \sum_{k\in\mathcal{U}_{r,d}} \theta_{i,k}^{(r,q,d)} = \sum_d \eta_d \sum_{r\in\mathcal{R}_d} \sum_{k\in\mathcal{U}_{r,d}} T_{i,k}^{(r,q,d)},$$

and

$$\textbf{Total Average Return} = \bar{F}(\mathcal{R},\mathcal{U}_\mathcal{R}) = \sum_d \sum_{r\in\mathcal{R}_d} \sum_{k\in\mathcal{U}_{r,d}} \bar{\theta}_{i,k}^{(r,q,d)} = \sum_f \bar{\eta}_d \sum_{r\in\mathcal{R}_d} \sum_{k\in\mathcal{U}_{r,d}} \bar{T}_{i,k}^{(r,q,d)} \qquad (8)$$

The total risk is thus given by

$$\textbf{Total Risk} = \bar{G}(\mathcal{R},\mathcal{U}_\mathcal{R}) = E\left[\left(\sum_d \sum_{r\in\mathcal{R}_d} \sum_{k\in\mathcal{U}_{r,d}}^{S} \theta_{i,k}^{(r,q,d)} - \sum_d \sum_{r\in\mathcal{R}_d} \sum_{k\in\mathcal{U}_{r,d}} \bar{\theta}_{i,k}^{(r,q,d)}\right)^2\right]$$

$$= \sum_d E\left[\left(\sum_{r\in\mathcal{R}_d} \sum_{k\in\mathcal{U}_{r,d}} \theta_{i,k}^{(r,q,d)} - \sum_{r\in\mathcal{R}_d} \sum_{k\in\mathcal{U}_{r,d}} \bar{\theta}_{i,k}^{(r,q,d)}\right)^2\right] = \sum_f E\left[\left(\sum_{r\in\mathcal{R}_f} \sum_{k\in\mathcal{U}_{r,d}} \theta_{i,k}^{(r,q,d)}\right)^2\right] - \sum_d \left[\left(\sum_{r\in\mathcal{R}_d} \sum_{k\in\mathcal{U}_{r,d}} \bar{\theta}_{i,k}^{(r,q,d)}\right)^2\right]$$

$$= \sum_d E[\eta_d^2]E\left[\left(\sum_{r\in\mathcal{R}_d} \sum_{k\in\mathcal{U}_{r,d}} T_{i,d}^{(r,q,d)}\right)^2\right] - \sum_d \bar{\eta}_d^2 \left[\left(\sum_{r\in\mathcal{R}_d} \sum_{k\in\mathcal{U}_{r,d}} \bar{\theta}_{i,k}^{(r,q,d)}\right)^2\right]. \qquad (9)$$

In a multi-objective portfolio optimization problem the main goal is to optimize simultaneously the return in (8) (maximize) and the risk in (9) (minimize), which can be written as:

$$\{\mathcal{R}, \mathcal{U}_{\mathcal{R}}\}_{opt} = \arg \max_{\mathcal{R}, \mathcal{U}_{\mathcal{R}}} [\bar{F}(\mathcal{R}, \mathcal{U}_{\mathcal{R}}), -\bar{G}(\mathcal{R}, \mathcal{U}_{\mathcal{R}})].$$

Since this type of optimization does not often have one unique solution, the concept of Pareto optimality is commonly used. A Pareto optimal solution can be briefly defined as the solution that is optimum for at least one of the components of the objective function [24]. To find the Pareto optimal trade-off region, the optimization problem can be conveniently reformulated by using the method of scalarization [24]:

$$\{\mathcal{R}, \mathcal{U}_{\mathcal{R}}\}_{opt} = \arg \max_{\mathcal{R}, \mathcal{U}_{\mathcal{R}}} f(\mathcal{R}, \mathcal{U}_{\mathcal{R}}),$$

where

$$f(\mathcal{R}, \mathcal{U}_{\mathcal{R}}) = \bar{F}(\mathcal{R}, \mathcal{U}_{\mathcal{R}}) - \mu \bar{G}(\mathcal{R}, \mathcal{U}_{\mathcal{R}}),$$

(10)

and where μ is the relative trade-off weight between risk and return. The value of μ will be crucial to the resource allocation process as it will allow for a direct control on the level of risk, which is directly associated, as shown earlier in this section, with the interference between secondary and primary users. The parameter μ will then control the number of allowed secondary transmissions in the system and thus also the impact on the performance of primary users. It is then foreseen here that an optimum value of can be obtained such that secondary transmissions do not significantly affect primary user transmissions, thereby maximizing sum throughput (primary + secondary). Since the optimization problem in (10) can be quite complex due to all the combinations of users, resources and networks, here we propose an iterative approach, where during the nth iteration the goal is to find only one combination of band-resource-users $(d, r, \mathcal{U}_{r,d})$ * that maximizes the following objective function:

$$\{d, r, u_{r,d}\}^* = \arg \max_{d, r, u_{r,d}} f[\tilde{R}_d(n), \tilde{U}_{\tilde{R}_d}(n)], r \notin R_d(n),$$

(11)

where $\tilde{\mathcal{R}}_d(n) = \mathcal{R}_d(n) + \{r\}$, $\tilde{\mathcal{U}}_{\tilde{\mathcal{R}}_d} = \mathcal{U}_{\mathcal{R}_d} + \mathcal{U}_{r,d}$, $\tilde{\mathcal{R}} = \{\tilde{\mathcal{R}}_1, \ldots, \tilde{\mathcal{R}}_D\}$ and $\tilde{\mathcal{U}}_{\tilde{\mathcal{R}}} = \{\tilde{\mathcal{U}}_{\tilde{\mathcal{R}}_1}, \ldots, \tilde{\mathcal{U}}_{\tilde{\mathcal{R}}_D}\}$.

The set of resources and scheduled users can then be updated as follows:
$\mathcal{R}_{d^*}(n+1) = \mathcal{R}_d(n) + \{r^*\}$, and $\mathcal{U}_{\mathcal{R}_{d^*}}(n+1) = \mathcal{U}_{\mathcal{R}_{d^*}}(n) + \mathcal{U}_{r,d}^*$ The iterative process stops whenever the objective function stops increasing, i.e. when $f[R_d(n+1), U_{\tilde{R}d}(n+1)] < f[R_d(n), U_{\tilde{R}d}(n)]$.

6.2.1 DAS Resource Allocation Problem

This subsection describes the sub-algorithm that optimizes the power levels, beam-forming vectors, the set of scheduled terminals and their MCSs in order to reduce intra-cell interference and maximize throughput. This algorithm complements the previously proposed radio resource allocation based on return and risk. The blending of the two schemes is given at the end of this subsection. Since all the operations in this subsection will be applied to all the existing networks, frequency bands and resources the notation q, r and d will be omitted hereafter. The objective is to reduce the following weighted least squares objective function:

$$e(\mathbf{P}, \mathbf{W}, \mathcal{M}) = \sum_{k \in \mathcal{U}} \epsilon_k (\tilde{\Gamma}_k - \gamma_k^{m_k})^2,$$

(12)

where P is the vector of stacked power levels of all scheduled users, W is the vector of stacked beam-forming phases, γ_k^{mk} is the target SINR to achieve transmission using the selected MCS m_k for user k, $\mathcal{M}$ is the set of selected MCS for all scheduled users, ϵ_k is the weight factor for terminal k:

$$\epsilon_k = \frac{\eta_d T_k}{\psi_k \left(E[\eta_d^2] E[(T_{i,k}^{(r, q, d)})^2] - \bar{\eta}_d^2 [T_{i,k}^{(r, q, d)}]^2 \right)},$$

where ψ_k and k is the queue length of user k. The general optimization problem can thus be stated as:

$$\{P, W, \mathcal{M}\}_{opt} = \arg \min_{P, W, \mathcal{M}} e(P, W, \mathcal{M}) \text{ subject to } P_l < P_{max}, \qquad (13)$$

where P_{max} is the node power constraint. Scheduling is addressed by deciding which power levels should be set to zero. Cell power constraint is not explicitly considered in (13) because it will be regulated with the modelling of inter-cell interference $\xi_{i,k}$ in (4).

6.2.2 Joint Power and Beam-forming Optimization

Due to the complexity of the optimization problem in (18), it is convenient to simplify it by dropping, for the time being, the scheduling and AMC components. This leads to the following joint power and beam-forming optimization problem:

$$\{P, W\}_{opt} = \arg_W \min \ e(P, W) \qquad\qquad \text{subject to } P_l < P_{max} \qquad (14)$$

To obtain the optimum power levels and beam-forming vectors, the method of gradient steepest descent is used.

$$P(n+1) = P(n) - \mu_p \nabla_p e(P, W, \mathcal{M})$$

$$W(n+1) = W(n) - \mu_w \nabla_p e(P, W, \mathcal{M}) \qquad (15)$$

where μ_p and μ_w are the step sizes that modify the convergence of the algorithm, and ∇ is the gradient vector operator. Step size is chosen so that the algorithm converges smoothly to the optimum solution. It is also possible to use other iterative algorithms that have been proved in the literature to converge to the MMSE solution (e.g., [16]).

6.2.3 Scheduling and AMC

Let us now explicitly integrate the WLS optimization scheme for power and beam-forming phases with terminal scheduling and AMC:

1. For each node in the central cell the best set of terminals is selected based on the measured channel gain. Initial beam-forming phases are calculated to maximize each user channel gain in the absence of interference.

2. Highest MCS is initially selected.

3. Vectors of power levels and stacked beam-forming phases are updated using gradient functions in (15).

4. If the optimum solution has been reached and the error function is equal to zero, then it means that all the SINR requirements have been met. Thus, the scheduled terminals are allowed to transmit with the selected MCS $\underline{M}$ and the algorithm goes to the next step. If the error function has not been minimized then the algorithm goes back to step 3 for another WLS iteration. If the optimum solution has been reached but the error function is not zero, it means that SINR requirements have not been met and then the user with the highest transmit power requirement must be allocated with a MCS with less SINR requirements $m_k(n+1) = m_k(n)1$. In case there is no other MCS with less requirements then the user is dropped from the iteration. The algorithm goes back to step 3.

5. If the maximum number of iterations has been reached then the algorithm stops. Otherwise it goes back to step 2.

This operation is also repeated for each cell inside a cluster of cells. Once the operation in one cell is finished, it proceeds to communicate its transmission parameters to the next cell in the cluster, which will use the updated information for an enhanced optimization of its own transmission parameters. This is repeated for all the cells in the cluster as illustrated in Fig. 2 until a given number of iterations has been reached and the algorithm converges. This iterative algorithm with communication between cells inside a cluster achieves MCC. The cluster considered in Figure. 2 consists of 9 cells. The RRM can use two frequency bands, one which is licensed to the system, and an additional frequency band that is normally used for indoor communication as shown

also in Figure. 2, but which can be accessed in an opportunistic fashion by the network under consideration thanks to the use of CR. The RRM algorithm is also presented in a flowchart in Figure. 5.

7. Results

Results of the RRM algorithm using the SLS described in previous sections are shown in Figure. 6 for different values of μ (different trade-off between return and risk). The figure shows the results for average throughput versus the transmit power settings. Note that the x-axis The results were calculated for a single radio resource unit per cell. In all simulations the return of a transmission in the licensed frequency is higher than in the unlicensed frequency. The opposite is used in the case of risk, as a transmission in the unlicensed band will always imply a higher risk than in the licensed band (i.e., priority is given to licensed or primary terminals). The results indicate that the proposed approach provides gains in terms of network metrics such as throughput and also in terms of economic metrics such as return and risk. The results also present the performance of a conventional cellular system with and without multicell cooperation and with and without beam-forming. A uniform linear array at each node with 8 elements has been used in the simulation with beam-forming. The results also show the performance of the system without cognitive radio, which in all cases is below the proposed algorithm. The parameters of the simulation are given in Table 1. In general the value of is observed to affect the performance of the resource allocation algorithm by providing different degrees of trade-off between return and risk. Since risk is closely associated with interference and the scenario used for simulation is highly susceptible to interference, then high values of μ yield better interference rejection and therefore higher throughput figures. The results also verify that the combination of technologies leads to a huge gain in capacity, which is key for future applications with increasing bandwidth demands.
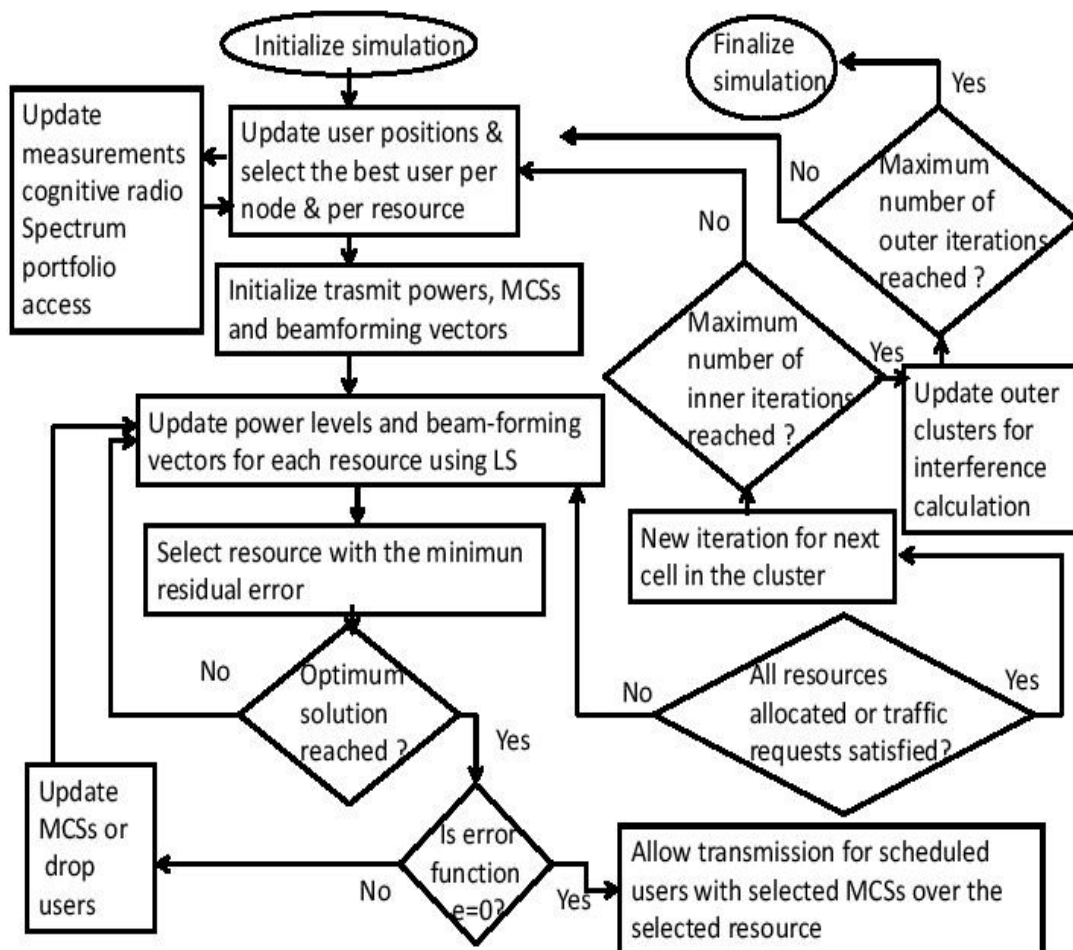
Figure 5. Flowchart of the proposed algorithm

Parameter	Value
Layout	Manhattan grid
Building width	100 m
Street width	20 m
Node street spacing	1
No. nodes per cell	9
No. cells per cluster	9
No. terminals	400
Frequency reuse	1
Channel model	WINNER B1
Antenna radiation patters	Directional
BS Antenna gain	15 dB
Mobile Antenna gain	0 dB
Wall penetration loss	8 dB
Simulator mode	Combined snapshot
Traffic model	Full queue
Number of frequency bands	2
Bandwidth	10 MHz
Subcarriers per symbol	1024
Data Subcarriers per symbol	720
Frame length	10 OFDM symbols
Radio resource unit (RRU)	720 sub-carriers
Radio resource unit (RRU)	10 symbols
Frame duration	5 ms
MCS feedback delay	2 TTIs
LSLI compression rule	EESM
Average return per bit (primary)	0.9
Average return per bit (secondary)	0.2
Average risk primary transmission	0.1
Average risk secondary transmission	0.5

Table 1. System modeling assumptions

8. Conclusions

A system level simulator (SLS) for Manhattan-grid dense urban wireless networks with DAS, MCC and CR has been presented. The paper presented the modules of the SLS that need improvement to deal with the new transmission paradigms and also with different licensing parameters of the spectrum portfolio provided by the operation of cognitive radio. An RRM algorithm was
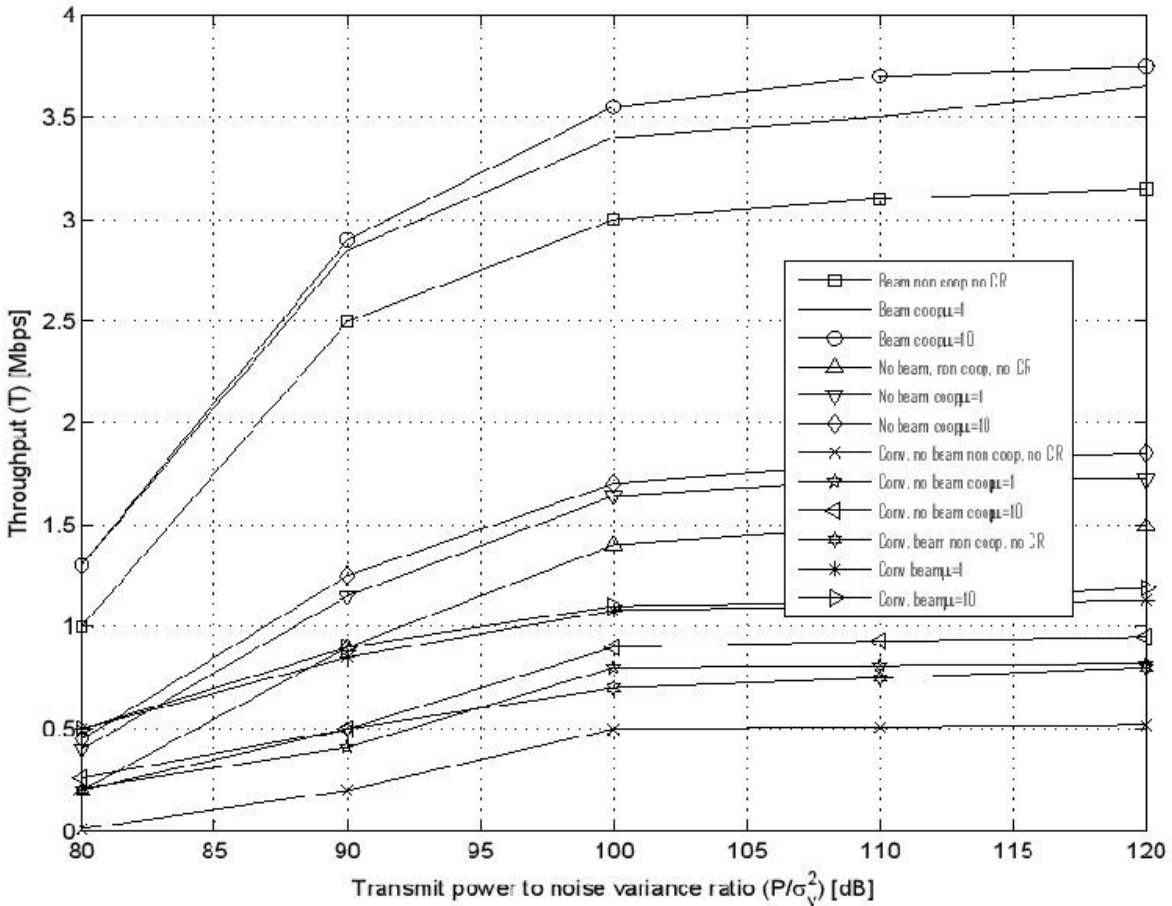
Figure 6. Average optimal throughput ($E[T]$) per cell *vs.* transmit signal-to-noise ratio $\dfrac{P_{max}}{\sigma^2_v}$ [dB] for the proposed algorithm in DAS and for conventional cellular systems.

developed to organize the radio resources across different distributed antennas of different cells and for different frequency bands with different economic/networking metrics. The optimization\algorithm was based on a multi-objective portfolio optimization approach to include economic information. An inner simulation loop based on an iterative weighted least squares optimization was used to obtain low-level network transmission parameters, such as Tx. power, beam-forming vectors, MCSs, and scheduled terminals. Economic information was used as the weights of the residual errors being minimized. An outer simulation loop was used to coordinate the resources among the different BSs of the deployment, thus achieving MCC. The results indicate that both economic and network optimality can be simultaneously met in the Pareto optimality sense.

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