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Abstract

The performance of wireless networks will experience a considerable improvement by the use of novel technologies such as distributed antenna systems (DASs), multi-cell cooperation (MCC), and cognitive radio (CR). These solutions have shown considerable gains at the physical-layer (PHY). However, several issues remain open in the system-level evaluation, radio resource management (RRM), and particularly in the design of billing/licensing schemes for this type of system. This paper proposes a system-level simulator (SLS) that will help in addressing these issues. The paper focuses on the description of the modules of a generic SLS that need a modification to cope with the new transmission/economic paradigms. An advanced RRM solution is proposed for a multi-cell DAS with two levels of cooperation: inside the cell (intra-cell) to coordinate the transmission of distributed nodes within the cell, and between cells (inter-cell or MCC) to adapt cell transmissions according to the collected inter-cell interference measurements. The RRM solution blends network and financial metrics using the theory of multiobjective portfolio optimization. The core of the RRM solution is an iterative weighted least squares (WLS) optimization algorithm that aims to schedule in a fair manner as many terminals as possible across all the radio resources of the available frequency bands (licensed and non-licensed), while considering different economic metrics. The RRM algorithm includes joint terminal scheduling, link adaptation, space division multiplexing, spectrum selection, and resource allocation.

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

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Abstract—The performance of wireless networks will experience a considerable improvement by the use of novel technologies such as distributed antenna systems (DASs), multi-cell cooperation (MCC), and cognitive radio (CR). These solutions have shown considerable gains at the physical-layer (PHY). However, several issues remain open in the system-level evaluation, radio resource management (RRM), and particularly in the design of billing/licensing schemes for this type of system. This paper proposes a system-level simulator (SLS) that will help in addressing these issues. The paper focuses on the description of the modules of a generic SLS that need a modification to cope with the new transmission/economic paradigms. An advanced RRM solution is proposed for a multi-cell DAS with two levels of cooperation: inside the cell (intra-cell) to coordinate the transmission of distributed nodes within the cell, and between cells (inter-cell or MCC) to adapt cell transmissions according to the collected inter-cell interference measurements. The RRM solution blends network and financial metrics using the theory of multi-objective portfolio optimization. The core of the RRM solution is an iterative weighted least squares (WLS) optimization algorithm that aims to schedule in a fair manner as many terminals as possible across all the radio resources of the available frequency bands (licensed and non-licensed), while considering different economic metrics. The RRM algorithm includes joint terminal scheduling, link adaptation, space division multiplexing, spectrum selection, and resource allocation.

Index Terms—Distributed antenna systems, system-level simulation, space division multiplexing, radio resource management.

I. INTRODUCTION

A. Background

Future wireless networks will require advanced schemes to cope 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 collocated 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 antennas/nodes are interconnected, via a coaxial cable or optical fibre, to the BS, where the main management and signal processing tasks take place. A related approach is given in MCC systems [2]. The BSs of different cells act themselves as the elements of the MIMO system by exchanging information between them. The performance of MCC is thus limited by the accuracy of the exchanged information [2].

Despite their advantages, these new technologies will only support one portion of the increasing demand for connectivity. This implies the need for more spectrum. Since spectrum is a limited resource, efforts are 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 allows unlicensed terminals to opportunistically access underutilized licensed

bands [3]. Therefore, opportunistic spectrum access via CR and improved signal processing via DAS-MCC are expected to mitigate the spectrum scarcity problem for future applications.

B. Open issues and previous works

Most of the existing literature on these technologies has been focused on physical (PHY) layer aspects (see [1]-[3]). However, several other issues need to be addressed before these technologies are 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 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 network. However, risks of service disruption and compatibility issues impede full testing in live networks. In addition, prototypes have the disadvantage of high costs and unrealistic deployments. Software-based *system-level simulators* (SLSs) have become a cornerstone in network design [4].

SLSs provide a virtual and flexible way to test new algorithms and collect system-level performance metrics (i.e. cell throughput, spectrum efficiency, revenue per terminal, etc.). Different approaches for SLS have been proposed in the literature. For example, SLS of a time-division spread CDMA (TD-SCDMA) system has 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 higher layers. The work in [7] simulated a TD-SCDMA system using the open-source OMNeT++ platform. As an alternative to these simulators, open simulator developed in the Aachen University was presented in [8]. SLS for optical-fibre-based DASs has been presented in [9] for the FP7 project FUTON using a tool called MOTION. The work in [10] has analysed round robin (RR) and maximum-carrier-to-interference (MCI) scheduling for DAS under different values of load and power. Improving on this, 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 in order to comply with a target signal-to-interference-plus-noise ratio (SINR) for each 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]. Distributed linear pre-coding and terminal selection for MCC has

are considered to be located at convenient positions on the streets (see Fig. 2). Therefore, the Manhattan deployment can be simply 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 Fig. 2 shows a cell in the Manhattan deployment with 9 nodes. The node at the center acts as the control unit for all the other nodes. Nodes are attached to the 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 Fig. 2 the superimposed squares show the limits of each cell. A multi-cell arrangement of 9 cells is also shown at the bottom of Fig. 2. The arrows indicate the information flow between cells for purposes of multi-cell cooperation.

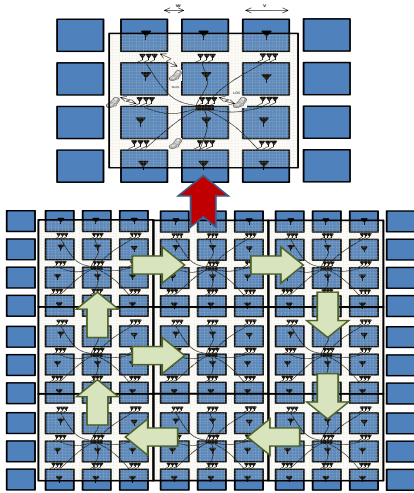


Fig. 2. Manhattan deployment scenario (single and multi-cell configuration).

Since the deployment scenario defines the space configuration where 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. 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. 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). Shadowing is the effect of objects that “shadow” some regions from correct signal reception.

The simulation results presented in this paper use the B1 model of WINNER project [16], 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 [16] 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 [17]. The shadowing model, which is assumed log-normal distributed, makes use of a bi-dimensional SoS with spatial correlation [17]. 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 [16]) has been used for implementation in the SLS. The radiation pattern of each antenna can also be configured by the user of the simulator.

IV. 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 parts. A 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 models. The link-layer simulator uses a granularity at the bit and symbol level, whereas the SLS uses a granularity at the radio-resource 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 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 collected BLER or PER metrics for all the terminals can be used to calculate system-level metrics. The LUTs are obtained via off-line PHY-layer simulation.

Let us now present a more formal representation of these mapping processes and interfacing models. We use the methodology described in [18] for the WINNER project, where the authors propose a generic link performance model that captures the performance of 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*

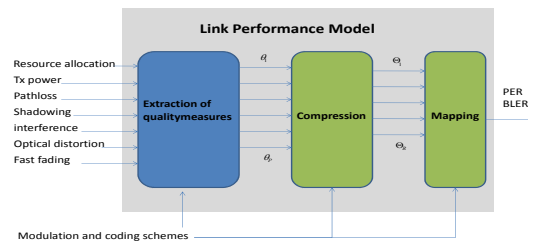


Fig. 3. Link-to-system level interface model.

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 with potentially different SINR conditions. The compression technique produces an equivalent SINR value for a block of sub-carriers which can be mapped directly to a LUT. 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 [19]. Several compression techniques have been proposed in the literature. In this paper, we use the exponential effective SINR compression method (EESM) with AWGN fixed mapping functions. The MCSs to be used correspond to the convolutional turbo coding scheme used in WiMAX [20]. The LUTs to be used for a block of 7200 sub-carriers for different modulation and coding schemes are given in [20], all calculated over AWGN channels. The optimum parameters for EESM are also given in [20].

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 considering RoF. These impairments are included in the entity dedicated to the extraction of the quality measures in Fig. 3.

V. TRAFFIC MODELS AND OFDMA FRAME DEFINITION

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, FTP calls, web browsing, and non-real-time video calls have been included in the simulator. Advanced mobility models based on Markov chains and random changes in direction and speed have also been included.

A. 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 and WiMAX). 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 sub-channels. 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 OFDM symbols and M sub-carriers. A basic radio resource unit to be used by the radio resource manager consists of a rectangular array of L sub-carriers and K OFDM symbols, as shown at the top

of Fig. 4. The frame definition in Fig. 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 Fig. 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 5ms [20].

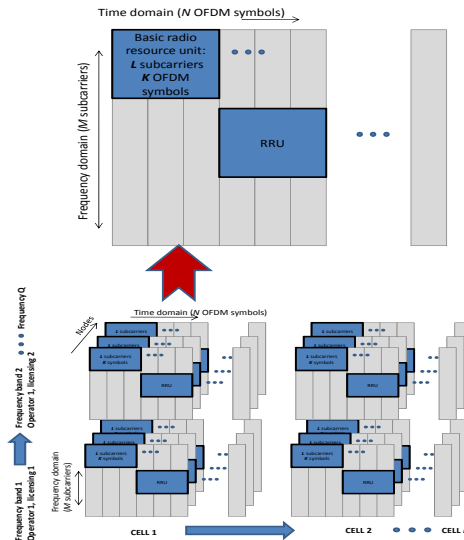


Fig. 4. Frame for radio resource allocation.

VI. RADIO RESOURCE MANAGEMENT AND RESULTS

The RRM functionality is at the core of the SLS and is in charge of two basic operations: the administration and allocation of radio resources, and the management of all the link and PHY-layer algorithms. The proposed RRM solution for DAS with MCC and CR implements a joint terminal scheduling, resource allocation, link adaptation, space division multiplexing, and opportunistic frequency selection algorithm. The algorithm is mainly intended for the down-link transmission. It also considers licensing/billing information of the different frequency bands using the theory of multi-objective portfolio optimization [21]. The portfolio optimization problem consists of searching for the optimum allocation weight for a set of assets that will maximize the economic *return* while minimize the *risk* (variance of the return). This is a multi-objective optimization problem, which in general, lacks of a unique solution. Instead, a set optimum solutions for a subset of objective functions, which are also known as the Pareto optimal frontier can be found [21]. The Pareto frontier can be found by the method of scalarization where a composite objective function is created by giving a different weight to return and risk components.

This indicates a trade-off between competing objective functions. Therefore, the objective of the RRM is to consider each radio resource unit of each node of each cell and of each available frequency band as an asset to be allocated using a scalarized multi-objective function. In the following, the sub-index i, j, k, l, m denotes terminal i , resource j , in the k -th node and in the l -th frequency band of cell m . This composite function can be thus written as:

$$\text{maximize } \sum F_{i,j,k,l,m}$$

where $F_{i,j,k,l,m} = p_{i,j,k,l,m} E[T_{i,j,k,l,m}] - \mu \alpha_{i,j,k,l,m} E[T_{i,j,k,l,m}^2]$ and where $p_{i,j,k,l,m}$ is the average return per information bit of transmitted information, $\alpha_{i,j,k,l,m}$ is the average risk, $E[T_{i,j,k,l,m}]$ and $E[T_{i,j,k,l,m}^2]$ are, respectively, the first- and second-order moments of the expected throughput. The measurements of CR are used to calculate the terms $E[T_{i,j,k,l,m}]$ and $E[T_{i,j,k,l,m}^2]$. Since this optimization problem is complex, we have to split it into several sub-problems with less complexity. The first step is to select the terminals to be served by each one of the nodes of each cell over each radio resource using the previous objective function. Then, for each radio resource, an iterative weighted least squares (WLS) optimization is used to adapt power levels, MCSs, and beam-forming vectors so as to comply with a SINR level for each scheduled terminal to transmit with the selected MCS with a given level of BLER. The weighting factors of the WLS optimization are given by the return and risk factors of each terminal over the given radio resource. The WLS optimization problem can thus be expressed as follows:

$$\text{minimize } e_{j,k,l,m},$$

where $e_{j,k,l,m} = \sum_i \beta_{i,j,k,l,m} \left(\tilde{\gamma}_{i,j,k,l,m} - \gamma_{i,j,k,l,m}^{(mcs)} \right)^2$ and where $\tilde{\gamma}_{i,j,k,l,m}$ is the measured SINR, $\gamma_{i,j,k,l,m}^{(mcs)}$ is the target SINR of the selected MCS, and $\beta_{i,j,k,l,m}$ is the weight for the optimization of the residual error. This weighting factor can be calculated as: $\beta_{i,j,k,l,m} = \frac{p_{i,j,k,l,m} E[T_{i,j,k,l,m}]}{\mu \alpha_{i,j,k,l,m} E[T_{i,j,k,l,m}^2]}$. The core of the WLS optimization presented above provides with the transmit power and beam-forming vectors that minimize the sum of residual errors weighted by the economical information. Once the solution has been reached, if the error function is not zero then either the set of terminals or their MCSs should be modified. Another iteration is started with updated settings by reusing the results of the previous stage, thus improving convergence speed. Conversely, if the error function is exactly or nearly zero, it means that all scheduled terminals can be allowed to transmit, as their target SINR with the selected MCS is satisfied in the given resource. This operation is repeated for each radio resource of the available frequency bands until the radio resources or the traffic data have been exhausted. The sequential optimization of each radio resource can be modified to give priority to those resources that require less optimization stages (smaller residual error). 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 Fig. 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 Fig. 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 Fig. 5. Results of the RRM algorithm using the SLS described in previous sections are shown in Fig. 6 for different values of μ (different trade-off between return and risk). 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 multi-cell 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 I.

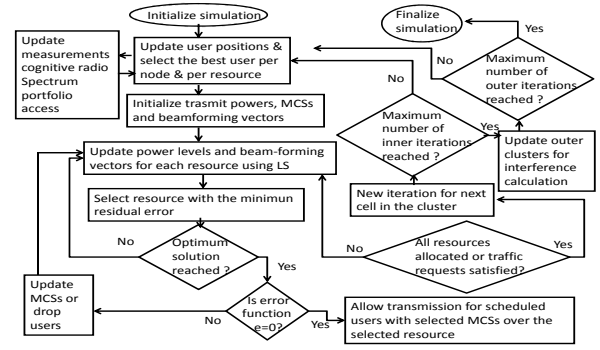


Fig. 5. Flowchart of the proposed algorithm.

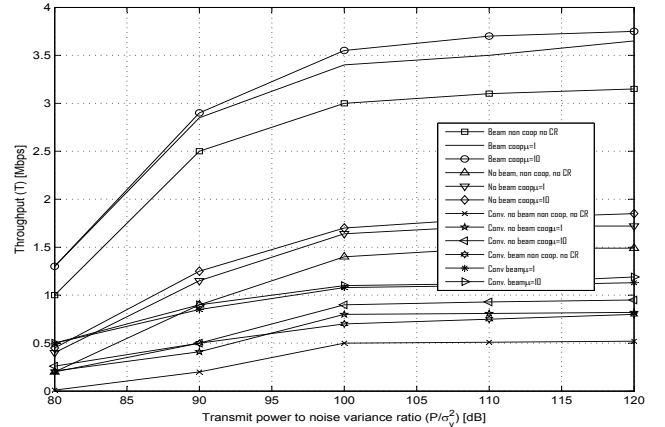


Fig. 6. Average optimal throughput ($E[T]$) per cell vs. transmit signal-to-noise ratio $\frac{P_{m,avg}}{\sigma_v^2}$ [dB] for the proposed algorithm in DAS and for conventional cellular systems.

VII. 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

TABLE I
SYSTEM MODELING ASSUMPTIONS.

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 patterns	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	$N = 10$ OFDM symbols
Radio resource unit (RRU)	$L = 720$ sub-carriers
Radio resource unit (RRU)	$K = 10$ 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

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 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 sense.

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