Modeling of Interference Maps for Licensed Shared Access in LTE-Advanced Networks Supporting Carrier Aggregation

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Abstract—Cognitive Radio based Dynamic Spectrum Access (CR-DSA) has been envisaged as the foremost solution to eliminate the impending false scarcity of the radio frequency spectrum and to combat the dramatic surge in mobile data traffic. Furthermore, the revolutionary concepts - Carrier Aggregation (CA) and Licensed Shared Access (LSA) - have been conceived to support higher data rates by aggregating bandwidth from different parts of the spectrum, and to provide for a predictable Quality of Service (QoS) through spectrum sharing, respectively, so as to enhance the performance of the current generation mobile communication systems.

However, an inevitable consequence of spectrum sharing is the interference induced upon the incumbent user. In this work, the prime focus of attention is on the mitigation of the interference caused by an LSA-licensed LTE-Advanced Radio Access Network (RAN) in the uplink (UL). To this end, we propose an interference management scheme based on Radio Environment Maps (REMs). Different approaches have been considered for the modeling of the requisite maps and a performance comparison between them by means of detection theory is presented. In conclusion, we prove the superior performance of the kriging spatial interpolation technique over the other approaches.

Index Terms—Carrier aggregation, licensed shared access, radio environment maps, spatial interpolation techniques

I. INTRODUCTION

Current spectrum licensing schemes are leading to the plausible scenario of false spectrum scarcity. This is mainly due to the fact that large sections of licensed spectrum channels, such as those used for TV broadcasting, satellite communications, etc., are generally underutilized - either spatially, temporally, or both [1], [2]. One of the promising solutions to this intricate problem is Cognitive Radio based Dynamic Spectrum Access (CR-DSA), where the unlicensed secondary users are allowed to access the licensed spectrum opportunistically and intelligently, provided that they do not adversely affect the performance of the incumbent users.

Carrier Aggregation (CA) is a method proposed by the 3rd Generation Partnership Project (3GPP) group as part of the LTE-Advanced Release 10 specifications to support the peak data rate requirements of 4G systems [3]. Through aggregation of bandwidth in the form of Component Carriers (CCs) from different parts of the frequency spectrum, a much wider transmission bandwidth of up to 100 MHz can be offered, thus improving the data rates considerably. Furthermore, as an extension to traditional DSA, Licensed or Authorized Shared Access (LSA/ASA) proffers a quasi-exclusive license to the secondary mobile broadband services to access the licensed spectrum, so that they may ensure a predictable QoS at their end terminals [4].

One of the main concerns over such a spectrum sharing set-up in the current mobile radio environment is interference. In the confines of this work, the focus lies primarily on the management of the interference caused by an LSA-licensed LTE-Advanced RAN on the incumbent user. To this end, we propose the implementation of an interference management scheme based on REMs [5], which would govern the usage of the acquired CCs in each cell located in an LSA-licensed network. Using the concept of REMs, we create a set of interference maps which depict the interference inducible on the incumbent users. The appropriate actions to mitigate the interference can be taken after comparing the computed interference maps with the criteria set by the incumbent users.

Alaya-Feki et al. [6] have proposed an interference cartography scheme to facilitate secondary spectrum usage. Using this concept, secondary networks can detect the presence of a primary network and use spectrum opportunities without affecting the performance of the primary networks. The spatial interpolation technique, kriging, was used to improve the performance of spectrum access systems. A comparison between spatial interpolation techniques was performed by Angjelicinoski et al. [7] towards the estimation of radio environments for efficient spectrum resource management. The performance analysis was performed using a Relative Mean Absolute Error (RMAE) metric.

In our work, a CA-based scenario is considered, where an LSA-licensed LTE-Advanced RAN may cause interference in one of the UL CCs acquired through spectrum sharing. To the best of our knowledge, this paper is the first to calculate spatial interference in the UL of an LTE-Advanced RAN. We propose different methods for the calculation of...
the requisite interference maps and analyze their performance compared to true interference maps computed using a brute-force approach. The performance evaluation is then done by means of detection theory for the interference thresholds specified by the incumbent users.

II. BACKGROUND CONCEPTS

A. Uplink considerations

In terms of spatial interference estimation, the UL poses certain additional challenges compared to the downlink (DL). Firstly, unlike the Base Stations (BS), the position of the User Equipments (UEs) varies over time due to their mobility. Hence, even the interference induced upon the incumbent user varies over time.

Secondly, the transmit power of the UEs and therewith, the received power from the UEs vary depending on the UE position within a cell as well as other environmental factors. The transmit power of each UE is calculated based on the homogeneous $P0$ and $\alpha$ values [8], as per the power equation (in closed form),

$$P_{t,u} = \min(P_{max}, P_{0} + \alpha \cdot L_v(q_u, \Theta_v) + 10 \cdot \log_{10}(M_u))$$

where $P_{t,u}$ is the total transmit power of UE $u$, $P_{max}$ is the maximum transmit power for any given UE, and $M_u$ is the number of Physical Resource Blocks (PRBs) which UE $u$ located in cell $v$ is allocated. $L_v$ defines the propagation loss experience by a UE in cell $v$, where the propagation effects - path loss and antenna patterns - are considered as functions of the UE positions $q_u$, and the antenna downtilt $\Theta_v$.

The received power in dBm, $P_{r,u}$ from a particular UE is then calculated by,

$$P_{r,u} = P_{t,u} + G_C$$

where $G_C$ is the coupling gain in dB, derived from the following equation,

$$G_C = G_v + B_v - L_a - L_b \cdot \log_{10}(d_{ref}) - P_{loss,v}$$

where the parameters $L_a$ and $L_b$ account for the path loss of the UE, and are specific to the BS which the UE is connected to. The distance $d_{ref}$ represents the reference distance at which the coupling gain is exactly equal to the parameter $L_a$. The parameters $G_v$, $B_v$ and $P_{loss,v}$ represent antenna gain, antenna beam pattern, and penetration losses, respectively, in cell $v$. Since we consider long term averaging for interference calculation, the effect of fast fading is negligible. The effect of shadowing is neglected due to feasibility considerations.

There are various methods available to estimate the position of the UEs, such as Received-Signal-Strength (RSS), Angle-of-Arrival (AOA), and Time-of-Arrival (TOA) based approaches, to name a few. Furthermore, according to the 3GPP Release 10 specifications, the UEs in a radio environment may be localised using their GPS coordinates. In our work, it is assumed that the location coordinates of each UE is known, either through their GPS data or one of the other methods mentioned above.

And lastly, the number of UEs present in a mobile radio environment, especially in an urban setting, is substantially large. All these issues increase the amount of measurement data communicated over the wireless links and lead to the infeasibility of the calculation of complete interference maps in the UL.

B. Spatial interpolation techniques

Spatial interpolation techniques are used to estimate the values at previously unobserved locations within a certain area using a minimal set of data collected by observing a random field. We have considered three of the most popular spatial interpolation techniques in this work - Nearest Neighbour (NN), Inverse Distance Weighting (IDW), and kriging.

1) NN: The nearest neighbour technique is the simplest spatial interpolation from a computational point of view, where the value assigned at each output location is the value of the nearest sample data point to that location. However, it is a naïve technique because it fails to consider the influence of the sample data points apart from the nearest neighbouring data point. Furthermore, the piecewise constant interpolation leads to discontinuity on the interference maps.

2) IDW: Inverse distance weighting is a deterministic spatial interpolation technique, where the value assigned at each output location is calculated based on a weighted average of the sample data points [9]. The interpolated value $\hat{Z}(x)$ at a certain location $x$, given the sample data set $Z_i = Z(x_i) \forall i \in \{0,1,\ldots,N\}$ using IDW is given by,

$$\hat{Z}(x) = \frac{\sum_{i=0}^{N} \lambda_i(x) \cdot Z_i}{\sum_{i=0}^{N} \lambda_i(x)}$$

where

$$\lambda_i(x) = \frac{1}{d(x,x_i)^p}$$

is Shepard’s weighting function determined by the distance $d$ between the output location $x$ and the sample point $x_i$, and the power parameter $p$, which is a positive real number.

3) Kriging: Kriging is a geostatistical estimator and a linear spatial interpolation technique developed by French mathematician Georges Mathéron based on the Master’s thesis of Danie G. Krige, whose name led to the concept’s terminology [10]. Similar to the IDW approach, kriging also uses a weighted average of the sample data points. However, instead of the inverse of the respective distances, kriging employs the spatial correlation between the sample data points to obtain the corresponding weights.

Assuming the same set of parameters described in the IDW approach, the interpolated value $\hat{Z}(x)$ using the kriging approach is given by,

$$\hat{Z}(x) = \sum_{i=1}^{N} \lambda_i(x) \cdot Z_i$$
The goal is to choose the weights such that the variance of the estimator, $\sigma^2_E(x)$, is minimized, given by,

$$\sigma^2_E(x) = \text{Var}\{\hat{Z}(x) - Z(x)\}, \quad (7)$$

under the constraint of unbiasedness, $\mathbb{E}\{\hat{Z}(x) - Z(x)\} = 0$.

The computation of the weight vector is based on an underlying concept called the semivariogram, or just variogram. The variogram is a measure of the statistical dependence between two points based on their values and the distance between them, and can be described as,

$$\gamma(h) \equiv \frac{1}{2} \mathbb{E}\{|Z(x + h) - Z(x)|^2\} \quad (8)$$

where $h$ is the lag distance vector between two points. A variogram model is used to represent the spatial characteristics of a sample data set. Due to space restrictions, a comparison between different variogram models cannot be presented here. In this paper, we have chosen the exponential variogram model for the kriging approach, represented by,

$$\gamma_{exp}(h) = n + c \left(1 - \exp\left(-\frac{3h}{r}\right)\right) \quad (9)$$

where, in the geostatistical jargon, $n$ is the nugget, $c$ is the sill, and $r$ is the range of the variogram. Furthermore, we assume that $Z$ is an isotropic process, i.e. $h = \|h\|$. If $K$ is the matrix of spatial variance between all sample points $\{x_i, x_j\}$, such that $K_{ij} = \gamma(\|x_i - x_j\|)$, and $k(x)$ is the vector of spatial variance between the output location $x$ and each sample point, such that $k(x)_i = \gamma(\|x - x_i\|)$, the vector of weights for the output location $x$ is computed using the equation,

$$\lambda(x) = K^{-1} \cdot k(x) \quad (10)$$

### III. CR-DSA ALGORITHM WITH CA

The CR-DSA algorithm employed in this work is based on the mathematical framework presented in [11]. Each LSA-licensed network has a few licensed CCs as well as a few additional CCs acquired through spectrum sharing. A Spectrum Policy Server (SPS) controls the activation/deactivation of the acquired CCs in each cell based on the average (transient) cell load, $\rho_{avg}$, as well as the interference caused by the UEs present in the cell.

Based on the LSA concept, each incumbent user stores its geographical constraints and the corresponding interference thresholds in an online database, accessible by the LSA-licensed operator, thus producing the exclusion zones. Fig. 1 describes the applied CR-DSA algorithm for a particular cell, where $\rho_{ma}$ and $\rho_{sd}$ represent the ‘may activate’ and ‘should deactivate’ thresholds, with $\rho_{sd} < \rho_{ma}$.

### IV. MODELING OF INTERFERENCE MAPS

For the calculation of the interference maps, three different methods are distinguished - ‘reference’, ‘basic’, and ‘spatial’. The reference method produces true interference maps which give a comprehensive and accurate overview of the combined RF received power from all the UEs in the radio environment at each output location. The basic and spatial methods serve as computationally feasible methods to obtain a rough estimate of the interference maps in lesser time and with reasonably fewer resources. The general detection theory parameters - hits, misses, correct rejections, and false alarms - are used to evaluate the performance of the basic and spatial methods based on the true interference maps.

#### A. Reference method

The reference method employs a brute force approach to (theoretically) compute the true interference maps, such that a very high accuracy of the values at the grid locations is guaranteed. The radio environment area is divided into a square grid with very high resolution for the utmost accurate interference maps. Computation of the interference maps takes place by considering the transmission power and the coupling gain of all the secondary UEs present in the radio system with respect to each grid location. At every grid location, the RF received powers from each active UE in the mobile environment is calculated using Eq. (2) and then added linearly, to obtain the combined sum of powers received at that grid location,

$$P_{r,sum} = 10 \cdot \log_{10}\left(\sum_{i=1}^{N_c} P_{r,lin}\right) \quad (11)$$

where $N_c$ represents the number of connected or active UEs in the mobile environment.

#### B. Basic method

In the basic method, instead of computing the RF received power at each of the grid locations, the interference radius of each secondary UE is calculated. It is the radius of the circular area over which the RF received power from the UE is above the specified interference threshold(s).

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**Fig. 1. Flowchart depicting the CR-DSA algorithm with CA**
In general, the interference radius $R_I$ is determined by substituting Eq. (3) in Eq. (2) and rewriting it as,

$$I_{th} < P_t + G + B - L_n - L_b \cdot \log_{10}(R_I/d_{ref}) - P_{loss}$$

and hence,

$$R_I \leq 10^{\left(\frac{P_t + G + B - I_{th} - L_n - L_b}{L_b}\right) \cdot d_{ref}}$$

(12)

where $I_{th}$ represents the interference threshold for the given exclusion zone. In turn, the basic interference map presents a binary overview of the mobile environment depending on whether a particular grid location is above or below the interference threshold(s).

C. Spatial method

The radio environment maps must statistically exhibit the characteristics of realistic environments [12]. By exploiting the spatial behaviour of the RF spectrum, artificial but realistic data sets can be generated with relatively low computational complexity. This method uses the three spatial interpolation techniques discussed above. The requisite interference maps are estimated using the spatial statistics present in a minimal set of available environmental data, i.e. the RF received power at select locations.

In order to obtain the required data, a set of sensor nodes is placed at different locations in the entire radio communication system. A uniform random deployment has been adopted in this work, where the geographical area of the radio system is divided into a coarse grid and the sensor nodes are evenly scattered over the area.

In the kriging approach, the sill and range parameters of the exponential model in Eq. (9) are calculated using a heuristic procedure based on the empirical variogram obtained from the observed sensor data. The \{sill, range\}-tuple, producing the modeled variogram which results in the least Root-Mean-Square Error (RMSE) with respect to the empirical variogram, is chosen for the estimation purposes. Subsequently, Eq. (6) is used to obtain the estimated value at each grid location based on the vector of weights computed using Eq. (10).

In order to lower the computational complexity and latency of the kriging and IDW approaches, only the data points present within a circle of interpolation radius are considered while computing the value at each output location. We assume that the data points lying at farther distances from the output point have a negligible influence on the final value. An optimal compromise between accuracy and complexity will result in a higher efficiency of this interference management scheme.

V. Simulation set-up

In this work, the radio mobile environment has been simulated on a dynamic system level simulator derived from the mathematical framework presented in [13]. A customary hexagonal layout with 21 cells is considered over a hexagonal simulation area of radius 3000m. Seven macro base stations, belonging to an LSA-licensed LTE-Advanced network, are equally spaced over the simulation area with an Inter-Site Distance (ISD) of 2100m to provide adequate coverage.

All the UEs considered in the simulation runs are LTE Release 10 UEs and capable of carrier aggregation. A UE deployment with three groups has been considered. One group of 1000 background users are deployed uniformly over the entire simulation area. Each background UE moves on a random path at a speed of 30 km/h. The other two groups are: a static group with 50 UEs, and a moving group with 50 UEs moving from north to south at a group speed of 100 km/h. Such a deployment primarily facilitates the visual comparison of different interference maps by distinctly localizing the UE hotspots.

Each UE can be in either of two states - connected or idle. A UE in connected state attempts to upload data with a fixed file size of 1MB. Upon completion, it automatically switches to the idle state. The UE waits in the idle state for a random period of time before switching back to the connected state; this process repeats through the entire simulation run. The waiting period of each UE in the idle state has been modelled as a random variable uniformly distributed between 0 and 30 seconds.

Each cell in the network has two CCs in the UL: the licensed CC of the network is always on, whereas the LSA-acquired CC is activated/deactivated based on the CR-DSA algorithm. Both the CCs have a bandwidth of 10 MHz, and therefore, allow for 50 PRBs each. In this work, only one exclusion zone with an interference threshold of $-85$ dBm has been considered. Fig. 2 shows the geographical location of the considered exclusion zone over the simulation area.

![Fig. 2. Depiction of the simulation environment with an exclusion zone](image-url)
VI. RESULTS AND ANALYSIS

Fig. 3 presents the plots with the performance statistics for the spatial interpolation techniques as well as the basic scheme. The statistics represent the average performance of each approach over 20 different UE distributions.

The performance of the basic scheme is independent of the sensor data and hence, remains constant on all the plots. The basic scheme fares substantially worse than the other three approaches with a hit and miss percentage of 44.59% and 10.61%, resp., as indicated in Table I. The main reason is the inability of the basic scheme to detect interference caused by multiple UEs, collectively. However, the reduced latency in the approach could be helpful in radio mobile environments in the rural areas, where the UEs are sparsely spread.

As expected, the performance of each spatial interpolation technique improves on all the plots with increase in the number of sensor nodes, before effectively reaching a plateau.

The kriging approach produces a considerably higher hit percentage compared to the interpolation techniques. NN has a lower accuracy than the other two interpolation approaches, especially with lesser number of sensor nodes deployed, since it neglects the influence of multiple sensor nodes on the value at a given location.

In Fig. 3d, we see that the performance of the basic scheme is much better than the other approaches with a correct rejection percentage of 44.04%. This is a direct consequence of the flawed performance with respect to the hit and miss percentages. Since the basic scheme only detects regions where one UE would cause interference, the number of correct rejections and thereby, false alarms should be optimal. The non-negligible false alarm percentage of 0.76% is primarily due to re-scaling issues during comparison.

For each spatial interpolation technique, the considerably higher false alarm percentage compared to the miss percentage
TABLE I: Performance statistics for $I_{th} = -85$ dBm

<table>
<thead>
<tr>
<th>Number of nodes</th>
<th>Hits [%]</th>
<th>Misses [%]</th>
<th>False alarms [%]</th>
<th>Correct Rejections [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>100</td>
<td>1000</td>
<td>100</td>
<td>1000</td>
</tr>
<tr>
<td>Krigeing - Exponential</td>
<td>52.12</td>
<td>54.88</td>
<td>3.08</td>
<td>6.66</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>0.32</td>
<td>1.60</td>
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<tr>
<td></td>
<td></td>
<td></td>
<td>6.86</td>
<td>37.94</td>
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<tr>
<td></td>
<td></td>
<td></td>
<td>43.20</td>
<td></td>
</tr>
<tr>
<td>NN</td>
<td>48.44</td>
<td>53.10</td>
<td>6.76</td>
<td>6.60</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>2.10</td>
<td>2.19</td>
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<tr>
<td></td>
<td></td>
<td></td>
<td>38.20</td>
<td>42.61</td>
</tr>
<tr>
<td>IDW</td>
<td>51.37</td>
<td>54.34</td>
<td>3.83</td>
<td>11.66</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>0.86</td>
<td>3.15</td>
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<tr>
<td></td>
<td></td>
<td></td>
<td>33.14</td>
<td>41.65</td>
</tr>
<tr>
<td>Basic scheme</td>
<td>44.59</td>
<td>10.61</td>
<td>0.76</td>
<td>44.04</td>
</tr>
</tbody>
</table>

points to the fact that all interpolation techniques tend to overestimate the lows. In Fig. 3c, when a lesser number of sensor nodes are deployed, the rather high false alarm rate of above 6% for each interpolation technique is a direct indication of overestimation.

As seen in Fig. 3c and 3d, the NN approach results in a correct rejection rate of up to 42.61% and a false alarm rate of 2.19%, which are comparable to the kriging results. Under the assumption that the sensor nodes are appropriately distributed over the entire simulation area, this favourable performance is an expected result since the attenuation of UE received power is characterized by a smooth logarithmic function.

However, IDW performs markedly poorer than the kriging approach with respect to the correct rejections and false alarms. This can be attributed to the fact that the kriging approach considers the variance between the sensor node data and the output point, and not just the distance between them. It weights the sensor nodes present in clusters differently to isolated sensor nodes, such that clustered sensor nodes having weaker correlation with the output point are effectively screened by isolated but strongly correlated nodes.

The main performance objective of each approach is to maximize the sum of hits and correct rejections, and minimize the sum of misses and false alarms. The kriging approach performs at best with a (hits + correct rejections) rate of up to 98.08% and in turn, a (misses + false alarms) rate of as low as 1.92%.

VII. CONCLUSION

The main objective of this work was to devise an interference management scheme to combat the interference induced by an LSA-licensee on an incumbent user in the UL. The modelling and estimation of the requisite interference maps and their performance analysis based on detection theory were at the forefront of this research work.

As the first contribution, a basic scheme is proposed for the computation of the interference maps, wherein the interference radius of each connected UE is measured depending on the interference threshold specified by the incumbent user(s). The main advantage of this approach lies in its simplicity, but it is flawed due to its inability to detect the interference caused by multiple UEs, collectively.

The second contribution investigates a more accurate approach, wherein the spatial statistics inherent in the environmental data have been exploited. By gathering minimal information from the radio environment through the deployment of a sensor node network, it was possible to estimate the required interference maps using the spatial interpolation techniques - nearest neighbour, inverse distance weighting, and kriging.

The spatial interpolation techniques produced a substantially improved performance over the basic scheme with respect to the hit and miss percentages, although the basic scheme outperforms them with respect to correct rejections and false alarms. However, the kriging approach produces an overall superior performance.

A critical consideration for future work is the effect of shadowing and other fading phenomena, which cannot be neglected in most indoor and also certain urban environments. This would make the interference management scheme more robust and more versatile.

REFERENCES