Abstract—Radio environment maps are a promising architectural concept for storing environmental information for use in cognitive wireless networks. However, if not applied carefully their use can lead to large amounts of measurement data communicated over wireless links, causing substantial overhead. We propose enhancing the basic radio environment map concept by spatial statistics and probabilistic models, enabling applications to benefit from environmental data while reducing overhead. In this paper we discuss the development of a topology engine, an agent in the CWN collecting and processing spatial information about the environment for storage in the REM. We discuss both technical and architectural issues in enabling such an approach, and outline some of the potential application scenarios for the topology engine.

I. INTRODUCTION

Cognitive radios and more generally cognitive wireless networks (CWNs) have emerged as a highly promising approach for optimizing performance of future communications systems. Recent advances towards deployment of dynamic spectrum access (DSA) networks based on the IEEE 802.22 standard is a particularly interesting outcome of this work [1]–[4]. However, there still remains several open research questions to be tackled in this domain. One of the most critical ones appears to be how to record, store and access relevant information about the environment to assist in functions such as collaborative spectrum sensing [5]–[8]. Radio environment maps (REMs) have been proposed as providing an architecture for such information collection and sharing [9]–[11]. The REM approach consists essentially of a database storing diverse information about the surroundings of a cognitive wireless network, such as transmitter locations, spectrum usage maps and so on. The key design decisions for such a database obviously are choosing what kind of information should be stored there, and in which manner it should be made available to the network.

In this paper we advocate the adoption of a statistical approach. For example, storing raw spectrum use information potentially requires very large amounts of data to be transferred between CWN nodes. For several applications, such as collaborative spectrum sensing, it is, however, sufficient to have access to few basic statistics of spectrum use over time and/or space. Statistics and probabilistic models are attractive especially in wireless environments since they can be expressed in a very compact form compared to the original data set. This means that communication overhead is reduced, leading to both improved performance due to reduction of overhead and extended system lifetime due to reduced power consumption. We focus in particular on spatial information, extending our earlier theoretical work towards applications in the REM context [12]–[15]. More specifically, we discuss design issues towards the development of a topology engine, an agent in the CWN collecting and processing spatial information about the environment for storage in the REM.

The rest of the paper is structured as follows. In Section II we give a concise overview of the spatial statistics most relevant to cognitive radio applications. In Section III we then discuss the key issues in the realisation of the topology engine, and how to enhance REMs with spatial statistics data. We discuss the general architectural issues related to this work in Section IV, and go through some of the expected application scenarios in Section V. Finally, we draw conclusions and outline issues for future work in Section VI.

II. SPATIAL STATISTICS FOR COGNITIVE RADIOS

In this section we shall give a short overview of the spatial statistics that are most relevant for cognitive wireless networks. We discuss first the characterisation of node locations, and then follow by discussing statistics relevant for characterising spectrum use over spatially extended regions. For a more detailed discussion also in the CWN context we refer the reader to [12]–[15].

A. Statistics of node locations

Suppose we are given a set of locations \( N = \{x_i\} \) of \( n \) nodes in some region \( D \subseteq \mathbb{R}^2 \) (see Figure 1). These locations could be those of primary users in a DSA scenario, or those of cognitive radios themselves in a network optimization scenario. They might be obtained from deployment databases, or be estimated by usual localization techniques based on, for example, received signal strengths. For simplicity we assume for now that the locations are known exactly. Especially for localization data this is obviously unrealistic, and we shall discuss the issues arising from inaccurate measurements in Section III. The problem we shall discuss in this section is now the statistical characterisation of \( N \) in a manner that allows reasoning about its structure even without complete knowledge of the locations of all the nodes in the region.

Commonly used statistical characterisations of \( N \) focus either on inter-point distances or on location correlations. Simplest examples of the statistics of the former type are
cumulative distribution functions of distances to the nearest neighbour, either from a randomly selected point of $D$, or from another point of $N$. These are the $F$ and $G$ functions of classical stochastic geometry [16]. Figure 2 shows the estimates for $F$ and $G$ for the set of node locations illustrated in Figure 1. Since the locations were obviously heavily clustered, the distances from randomly selected points of $D$ are typically much longer than from neighbouring nodes as shown in the figure. Such statistics are very relevant to CWNs especially in the dynamic spectrum access scenario, since they allow, for example, reasoning about distances to the nearest primary user or a client thereof.

Simplest example of a statistic characterising location correlations is the pair-correlation function $\xi(r)$ defined by the joint probability density

$$dP = \nu^2 (1 + \xi(r)) \, dA_1 \, dA_2$$

of finding one point in each of the two area elements $dA_1$ and $dA_2$ at distance $r$ apart ($\nu$ is the intensity of the locations, giving the mean number of points per unit area). If the locations were uniformly random, we would obviously have $\xi(r) \equiv 0$. At length scales in which clustering is present, $\xi$ obtains positive values proportional to the level of clustering of locations. This is clearly visible in Figure 3 showing an estimate of the pair correlation function for the locations depicted in Figure 1. The figure also shows the small amount of negative correlation introduced by the “gaps” between the clusters roughly at length scales $r \in [0.1, 0.15]$. Pair correlation function can also be used to estimated the number of expected neighbours of a randomly selected nodes, a highly relevant quantity in, for example, interference estimation and optimization of medium access control protocols.

B. Random fields

In addition to location data, CWNs are often envisaged to make measurements of, for example, spectrum use over potentially large regions. Spectrum use can be modelled as a random field, that is, by assigning a random variable $Z(x)$ at each point $x$ of a region $D$ with possibly distance-dependent correlations between nearby values. The value of $Z$ can denote, for example, the mean PSD measured at that location, or practically any other continuous metric characterising spectrum use. For collaborative spectrum sensing applications most important statistics of $Z$ are of correlation type. Nodes that are too nearby as measured against the correlation length of $Z$ would gain little additional information from simultaneous spectrum measurements, and could thus refrain from collaborating in case such correlation information is available.

Classical statistic well suited for estimating the correlation lengths in $Z$ is the semivariogram

$$\gamma(s-t) = \frac{1}{2} \text{Var}\{Z(s) - Z(t)\}$$

where $s, t \in D$. Occasionally the covariance function

$$C(u, v) \equiv \text{Cov}\{Z(u), Z(v)\}$$

is used instead, but the semivariogram is in general more robust against estimation errors [17]. Typical shape of the semivariogram is illustrated in Figure 4, with the $x$-axis...
indicating the length scale \(|s - t|\). The key parameter in our context is the range of the semivariogram, which indicates the distance at which the samples of \(Z\) become uncorrelated. The shape of \(\gamma\) can further be used to reason about the magnitude of correlations at smaller distances.

III. FROM REMS TOWARDS TOPOLOGY ENGINE

Having taken a brief detour in spatial statistics, we shall now return to the issue of radio environment maps and enhancing them with information obtained from the envisaged topology engine. Essentially three types of spatial or topology information can be stored in a REM. The simplest of these is the individual measurements themselves, either directly or after some basic filtering. Another type of information is various statistics of the measurements, such as the spatial ones discussed in the previous section. Third type we shall consider is various models of the phenomena of interest. We shall consider both statistics and models in relation to REMs in more detail in the following.

Storing and exchanging statistics is obviously for any larger data set more efficient than exchanging raw data itself. The main challenge is how the statistics are obtained in the first place. One option is to carry out comprehensive measurements, gather all the data into a single location (physical or virtual) in, for example, a backend system, and estimate the statistics of interest there. Such an approach has the advantage of accuracy, and it also enables further statistics to be computed later from the raw measurements provided they are retained in the system. The main disadvantage is the communication overhead and potentially large amounts of storage needed. Techniques such as opportunistic communication [18], [19] could be used to transmit results only when a high speed connection is available to the backend system, but such optimizations do not address the basic problem of high overhead.

An interesting alternative to the above approach is the online estimation of statistics of interest. For example, a mobile terminal can easily collect information on density of nodes over the regions it traverses, and these density fluctuations can in turn be used to estimate correlations in node locations. Similarly semivariance of spectrum occupancy could be estimated by collecting information over time. Also, given some knowledge on propagation environment and technology used, RSS (Received Signal Strength) readings from beacon messages could be used to estimate the distance distribution functions of node locations. Such estimation of statistics by exploiting the naturally present dynamics of the network is still a relatively undeveloped subject, but the foundations exist in the spatial sampling literature (see, for example, [17], [20] for discussion and references). Selection of robust statistics is obviously key. Figure 5 illustrates a localization problem in a shadow fading environment. The quality of the raw location measurements is obviously not very good, especially at higher distances from the measuring node. However, the \(J\)-statistic defined by

\[
J(r) \equiv \frac{1 - G(r)}{1 - F(r)} \tag{4}
\]

yields almost exactly correct results on localised data despite the individual errors as can be seen from Figure 6.

The statistical approach to REMs can be further enhanced by application of models of the various phenomena taking place in networks. Often processes such as connection formations, activity patterns of primary users, node deployments, shadowing and fading etc. can be described with relatively high degree of accuracy by choosing a member of a small family of models and selecting the parameters in appropriate manner. The selection between models for the given characteristic and environment can again be made based on individual measurements or through application of appropriate statistics. Another interesting possibility is the development of dedicated system recognition mechanisms tailored for the
problem at hand. For example, we have successfully applied simple $k$ nearest neighbours classifier on RSS measurements to discriminate between different node location models. Models can also be useful in estimating various derived quantities from raw measurements, for example distances based on models of signal propagation.

IV. Architectural Implications

Enabling some of the functionalities discussed in the previous section require at least some support from the CWN architecture. First, the information gathering requires interfaces and protocols. This has been well understood by DSA research community and several different standardization approaches are on-going. However, the problem is deeper than a simple standardization. As the information for topology engine can be gathered potentially from many different sources it would be highly beneficial to have technology-independent interfaces and data representation standards. These would become a significant enablers and would lower the complexity of system implementation.

Architectural implications and decisions affect the scope of different interfaces and standardization methods. For example, if we suppose that REM measurements are mostly done by dedicated spectrum monitors or new cognitive radios it means that we need to define interfaces for devices that are designed for dedicated purposes. However, if we believe that information will be provided generally by different devices, including user terminals, this implies that heterogeneity in the networks is high and defining standardized interfaces become very important. This is not a trivial problem to solve, e.g., at the present time even implementing something so simple as collecting RSSI (Received Signal Strength Indicator) or SNR (Signal to Noise Ratio) information is quite complex. Even in the case of WiFi (IEEE 802.11) products the manufacturers do not, in general, provide open interfaces for programmers and are using highly proprietary methods for coding their information. The has been relatively little work on addressing this general problem, one of the rare exceptions being so called Unified Link-Layer API work [21].

The topology engine concept generates also other architectural challenges especially if we aim at to more open architecture, where a lot of data were communicated. One of the useful basic premises would be to report radio environmental conditions from roaming cognitive radio terminals towards information gathering points. This would mean that we transmit periodically tuples that are in the form of (terminal-ID, location, time, measurement-Information). However, this would imply also that the radio location and its movements are exposed to outside entities. This is, of course, done also in the case of current cellular networks but the question here is that this data would be actually used for modeling and the actual user and use of such data should be clearly defined.

Another important architectural consideration is the need to exchange information between CWN nodes themselves and with possible backend systems operating the core REM functionality. For the first part the relevant architectural component is a well-defined control channel, enabling access to measurements and configuration information across the network. In relation to the backend systems and REMs themselves, the key functionality to be defined in the architectural level is the format for storing and representing statistical and model-based knowledge gathered by the topology engine. Clearly a simple data representation approach suitable for raw measurement data would be insufficient for this case, especially considering the requirements for appropriate annotation of the statistical and model data with appropriate metadata based on which reasoning about accuracy and domains of validity can be made.

Our own current work is focusing on understanding hierarchical architecture for topology engines and REMs. The hierarchy can be understood both at logical and architectural plane. First, different topology engines and optimization methods require varying abstraction, or accuracy, levels and this needs to be supported in order to minimize resource usage. Second, the architecture itself needs to support different topology information gathering mechanisms. This means that both measurements can be done at the different levels (terminal, specific observing nodes etc.), and also data gathering and processing will be hierarchical. Most likely the information is also collected and modeled within different administrative domains, and it will be an architectural challenge to see how one could merge such information.

Finally, REMs and generally topology engines cannot be implemented easily as completely distributed architectures. Several reasons, such as needed computing power, need for privacy (for user locations), the amount of data involved in, strongly suggests towards hierarchical and partially centralized architectures, where REM and Topology Modeling servers will provide infrastructure based services for cognitive radios. In the case of DSA scenarios these servers could, but does not need to, be co-located with spectrum policy servers.
V. Example Applications and Usage Scenarios

REMs and the topology engine concept can serve as building blocks for many applications in cognitive wireless network by providing the non-local information required by the cognitive radio nodes to infer, predict and optimize their performance. In this section we shall discuss some of the potential benefits in greater detail. We first describe the application categories and then present an example scenario.

A. Application categories

We study the applications of REMs and the topology engine under three broad categories based on type of functionality it provides to the end-application: (1) Network planning; (2) Connection optimization; and (3) Localization. It is to be noted that a single application may use REM and topology engine for effectively carrying out more than one type of functionality.

1) Network planning: Network planning applications use the monitored radio activity information to network-wide performance benefits. They generally operate at larger time periods. Some applications under this category are network monitoring and provisioning.

Monitoring and provisioning applications use the spatio-temporal data to monitor network load and traffic-engineer the network. For example, the network service provider uses such data for negotiating the cost for leasing secondary spectrum band from other spectrum licence owners. They might introduce new policies that choose an appropriate spectrum band based on the current observed load. It also aids updating the infrastructure of the network to support the observed load (e.g. installing cognitive routers or base stations).

2) Connection optimization: These applications utilize the data from REMs at a fine time-granularity to detect, predict and optimize performance of a single connection or node. Dynamic spectrum access, connectivity maintenance, congestion control and traffic prediction are some of the common examples.

Complying to interference related policies set by spectrum license owners require accurate estimation of primary user’s activity. Distributed sensing mechanisms are effective in radio activity detection in the neighborhood [22]. REMs and spatial statistics provide the vital information that is necessary building accurate sensing mechanisms. Thus information also helps connectivity maintenance applications for inferring topology and adjust various low-level parameters like protocol negotiation (e.g. contention-free or contention based protocol), protocol parameter negotiation (e.g. channel, transmit power, etc.).

The information from REMs and topology engine forms a fundamental parameter even in classical interference-estimation protocols [23]–[25]. Precise detection of interference relationships between the nodes [23] require the radio information (e.g. received signal strength) of the network neighborhood. Topology engine with information in REMs assists in building such fundamental interference relationships between the nodes of a network.

3) Localization: Finally, applications might use the topology engine to discover the geographic coordinates of a node. Localizing using the spatial data of radio devices is cheaper and can be combined with other topology information like maps of the building [26]. Moreover, this might be the only feasible localization mechanism in urban environments where GPS signal is unavailable (e.g. indoor environments).

B. Example application

We describe a usage scenario of the application of topology engine in a cognitive environment. Consider a scenario where a company executive occasionally travels between two neighboring company locations in a car. The travel route ranges from densely populated urban area to country roads, thus a crossing through a wide range of wireless environments consisting of home wireless devices, TV transmitters, cellular operators, metropolitan WiMAX and mesh networks. Her associates use this travel time for updating her about the activities through video-conference, which she accesses through a cognitive radio enabled PDA. A primary requirement of during this conference is an assured QoS for this application at a reasonable price.

First, provisioning for this application is greatly optimized by predicting the current location. The localization can be intelligently executed by using the GPS, and switching to wireless radio based localization in urban environments (the localization problem). Second, the topology engine gathers the spatio-temporal information of the wireless activity in the planned route by querying REM. The expected activity is used for reserving the appropriate spectrum for near-future access. This information is also used to optimize network parameters; an appropriate protocol stack and their parameters are chosen and initialized by the cognitive radio based on this information (connection optimization problem). Third, spectrum bands are constantly monitored to possible use of secondary spectrum in case of an unexpected burst of wireless activity in the current one. Spectrum detection mechanisms use the information gathered by local sensing and the REM data aid in detecting these activities. The radio immediately switches to best secondary spectrum and protocol stack, thus enabling a soft-handover that sustains the video-conferencing capacity and delay requirements.

The service providers regularly observe the activities of their clients and dynamically optimize the service quality by using a custom topology engine (the network monitoring application). Providers create dynamic policy rules, which includes the pricing constraints, for leasing the spectrum bands from respective license owners when the QoS parameters of their clients cannot be satisfied.

VI. Conclusions

In this paper we discussed the enhancement of the radio environment maps by means of spatial statistics and models obtained through a topology engine, which is envisaged as an agent in the CWN collecting and processing spatial information about the environment for storage in the REM.
We gave a short background overview on the underlying theoretical concepts the envisaged techniques would rely on, and discussed the key design and implementation issues. We also outlined broader architectural considerations arising from the work, and discussed some of the foreseen application scenarios. The topology engine work is core part of our current research activity both in the theoretical domain as well as in practical implementation work. In the near future we expect to complete first prototype implementation of the framework, and start testing some of the approaches discussed in the text especially focussing on the 2.4 GHz ISM band. Widespread use of especially Wireless LANs in that band make it an interesting and rich experimental environment without the need for integration of additional transceivers to the prototyping platforms. However, our longer term goal is the integration of the topology engine core with flexible software defined radio platforms such as WARP or USRP2 [27], [28].

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