Neural Network Cognitive Engine for Autonomous and Distributed Underlay Dynamic Spectrum Access

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Abstract—Two key challenges in underlay dynamic spectrum access (DSA) are how to establish an interference limit from the primary network (PN) and how cognitive radios (CRs) in the secondary network (SN) become aware of the interference they create on the PN, especially when there is no exchange of information between two networks. These challenges are addressed in this paper by presenting a fully autonomous and distributed underlay DSA scheme where each CR operates based on predicting its transmission effect on the PN. The scheme is based on a cognitive engine with an artificial neural network that predicts, without exchanging information between the networks, the adaptive modulation and coding configuration for the primary link nearest to a transmitting CR. By managing the tradeoff among the effect of the SN on the PN, the achievable throughput at the SN and transmission overhead, the presented technique maintains the change in the PN relative average throughput within a prescribed maximum value, while also finding transmit settings for the CRs that result in throughput as large as allowed by the PN interference limit. Moreover, the proposed technique increases the CRs transmission opportunities compared to a scheme that only uses an estimate of the modulation scheme.

I. INTRODUCTION

The cognitive radio (CR) paradigm is seen as a solution to the spectrum scarcity problem stemming from growing needs from wireless applications together with the inefficient nature of the established static spectrum allocation policy [1]. A CR is an intelligent wireless device with the ability to autonomously gain awareness of the wireless network environment and to learn how to adapt its operating parameters to best meet the end-user goals [2]. As a result, CRs had frequently been considered as an enabling technology for dynamic spectrum access (DSA). Through DSA a network of CRs, called the secondary network, operates by sharing the radio spectrum with a primary network which is the incumbent owner of the spectrum band in use. Of the three main DSA approaches (overlay, underlay, and interweave DSA [3]), this paper focuses on underlay access. The underlay DSA allows CRs in the secondary network (called hereafter “secondary users” - SUs) to transmit over the same spectrum band being used by the PN by limiting their transmit power level so that the interference they create on the PN remains below a tolerable threshold [4].

Despite having been studied for over a decade, the main challenges in underlay DSA remain on how to establish the interference threshold for the PN links and how the SUs autonomously become aware of the interference they create on the PN, specially when following an ideal operating setup where there is no exchange of information between primary and secondary networks. In order for the secondary network (SN) to assess its effect on the PN, researchers have proposed different techniques that make use of the information from the receiving PU that is sent over a feedback channel. Since feedback channels are part of most wireless communication standards [5], [6], researchers have used them under the assumption that the SU can access these channels from the PN so as to assess the effects of the SN on PN links. For example, in [7]–[9] the control feedback channel, and in [10], [11] the ARQ feedback channel, have been used by a CR to extract information about the primary link. Yet, by relying on listening to feedback channels in the PN, these works share a setup where primary and secondary networks are not completely separated and exchange information with each other. In contrast to these works, the technique to be presented in this paper does not rely on any information exchange between the networks but, instead, takes advantage of the use at the primary network of adaptive modulation and coding (AMC), a technique that adapts the modulation scheme and channel coding rate according to the quality of the transmission link.

The use of AMC has been part of all high performance wireless communications standards developed over the past two decades and, thus, expected to be used by a typical PN [12]–[14]. Since the AMC mode chosen for transmission depends on the link’s signal-to-interference-plus-noise ratio (SINR), by estimating this mode by a CR, it is possible for a CR to learn the SINR experienced by a primary link. More specifically, in this work we propose an underlay DSA technique that uses as input an estimation of the adapted modulation scheme being used at the PU transmitter and predicts as an indication of primary link’s SINR its full AMC mode. A CR can estimate the PU’s modulation scheme during spectrum
sensing by listening passively and applying signal processing technique (not the subject of this work) on the feedback channel. There is a large volume research on modulation classification techniques that could be used to generate the input for our proposed underlay DSA technique. The work in [15] studied modulation classification based on second and higher order time variant periodic cumulant function of the sensed signal which required prior knowledge of the signal parameters. Authors in [16] used the same framework to perform signal preprocessing, along with utilizing artificial neural networks to address the issues associated with classification when the signal parameters are unknown. The work in [17] proposed a fully automated modulation classification scheme which employs two stages of signal processing to classify the AMC feedback signal. In this paper we assume that each SU applies the technique proposed in [17] on the nearest primary link to infer its used modulation scheme.

Moreover, leveraging the use of adaptive modulation in the PN will allow us not only to assess the effects of the SN on the PN, but will also allow us to establish the PN interference threshold. As shown in [18], the use of adaptive modulation allows for the background noise to increase up to a certain level before the average throughput in the network starts to decrease. In the context of underlay DSA where the PN does not exchange any information with the SN, the interference imposed on the PN by an underlay-transmitting CR can be seen as a background noise, that can be increased up to a level which does not affect the average throughput in the primary network. Therefore, a CR can become aware about its created interference on the primary link and decide on its transmit power by inferring the experienced throughput of the primary link and detecting any change in it. However, in a general setting with no exchange of information between the primary and the secondary network, while a CR can apply signal processing techniques (e.g. techniques such as those in [16] or [17]) to infer during spectrum sensing the modulation order being used by a primary transmitter, there is no previous known practical way to infer the experienced throughput of the primary link.

The main contribution of this paper is to present a fully autonomous and distributed underlay DSA technique where CRs set their transmission parameters so as to minimally affect the primary network based on the CRs ability to estimate the throughput (equivalently, the full AMC mode) of a primary link in the absence of secondary transmissions and for different SU transmit power settings. The technique is based on the use of a non-linear autoregressive exogenous neural network (NARX-NN) cognitive engine in the SU that has as input the estimated modulation order in the nearest primary link, and as output the estimation of the throughput experienced at the same primary link. As such, the novelty of this work resides in presenting a technique to infer, without tapping into feedback or control channels from another network, the modulation order and the channel coding rate used in the transmission of the other network, and to leverage this inference in the realization of a fully autonomous and distributed underlay DSA scheme.

As noted, the main component of the technique presented in this paper is a neural network-based cognitive engine. It is worth noting that there has been large number of works that have applied neural networks for various communication tasks such as channel decoding, estimating the features of the user channels and predicting the anomalies for wireless sensor networks [19]–[21]. For CRs, to overcome scarcity in the radio frequency spectrum a feed forward neural network has been used to predict the spectrum occupancy status [22] and in the design of a medium access control (MAC) protocol [23]. Compared to feed forward neural networks, recurrent neural networks can better represent the behavior of dynamic systems such as spectrum availability over time [24]. The inherent feedback connection links in recurrent neural networks help keep track of previous states of the system and make this type of neural networks suitable for prediction tasks (even beyond those in communication systems) based on previous observations. Although many recurrent neural networks have been investigated for one step ahead prediction, NARX-NN, as a type of recurrent neural networks, were proven to be powerful for multi-step prediction as well as pattern recognition and classification applications [25]–[27]. The work in [28] has shown that NARX-NN models also provide promising qualities for the prediction of chaotic time series, therefore they were applied to predict a variable bit rate (VBR) video traffic time series [29].

Since the effect of SUs transmissions on the primary network is an example of a dynamic system and, in addition, throughput in the PU can be seen as a time series with a temporal dependency, in this work we choose the NARX neural network-based underlay DSA technique. We propose a new learning-based approach that treats the input and output of a resource allocation algorithm as an non-linear unknown mapping and uses a NARX-NN to approximate it.

As noted, part of the novelty of our work is the estimation of effective throughput on a link of a separate network, which in turn allows a CR to estimate not only modulation order but also channel coding rate of a primary link. This ability enables a finer control knob for a more accurate power allocation with less harmful effect on PN transmissions as compared to techniques that rely only on the estimation of modulation order (from applying signal processing on the transmission waveform).

Our simulation results show that the presented technique is able to maintain the change in PN relative average
throughput within a prescribed target maximum value, while at the same time finding transmit settings for the SUs that will result in as large throughput in the SN as could be allowed by the PN interference limit. As such, while succeeding in its main goal of autonomously and distributively determining the transmit power of the SUs such that the interference they create remains below the PN limit, our proposed technique is also able to manage the tradeoff between the effect of the SN on the PN and the achievable throughput at the SN. Specifically, simulation results will show that for the proposed system with a target PN maximum relative average throughput change of 2%, the achieved relative change is less than 2.5%, while at the same time achieving useful average throughput values in the SN between 132 and 50 kbps. In addition, it will be seen that the implementation of a variation of the proposed scheme that reduces three times the overhead from transmitting probe messages still exhibits the ability to finely control the effect on the primary network throughput, although, as is to expect, it increases by 1%, only at low PN loads, the relative average throughput change compared to the case of sending all probe messages. Moreover, it will be seen that the enabling factor in the operation of the proposed technique is the ability of the NARX neural network cognitive engine to accurately predict the modulation scheme and channel coding rate used in a primary link without the need to exchange information between the primary and the secondary networks (e.g. access to feedback channels). This ability also results in a significant increase in the transmission opportunities in the SN compared to schemes that only use the modulation classification information.

The rest of this paper is organized as follows. Section II describes the overall system setup. The rationale on how AMC can be leveraged to address the main challenges associated with underlay DSA is outlined in Section III. Section IV describes our proposed distributed underlay DSA technique. Simulation results are presented in Section V followed by conclusions in Section VI.

II. SYSTEM SETUP

We consider a primary network with $N_P$ active primary links coexisting with $N_S$ active secondary links, with both networks transmitting over the same frequency band. In this section we focus on describing the setup for the PN, which is incumbent to the considered radio spectrum band. Section IV will present the underlay DSA scheme implemented in the SN. We assume that the PUs receive service from $N_{PBS}$ transmitting base stations (BSs), and we call the ratio $N_P/N_{PBS}$ as the primary network load. Each PU is assigned to the base station that presents the best channel gain. In addition, AMC is used in all transmissions (primary and secondary networks). This means that a transmitter has information about its link quality, in terms of SINR, and based on this assessment chooses from a set of options, the modulation scheme and channel coding rate that results in highest throughput while at the same time meeting a maximum bit error rate (BER) limit.

Let $P_{ij}^{(p)}$ denote the transmit power in the $i$th active primary link ($i = 1, 2, \ldots, N_P$) and $G_{ij}^{(pp)}$ be the path gain from transmitter $j$ to receiver $i$, all in the PN. Then, in the absence of the SN, the SINR in the $i$th primary link (which is used to decide the AMC mode) can be written as,

$$\gamma_{i}^{(p)} = \frac{G_{i}^{(pp)} P_{i}^{(p)}}{\sum_{j \neq i} G_{ij}^{(pp)} P_{j}^{(p)} + \sigma^2}, \quad i = 1, 2, \ldots, N_P,$$

where $\sigma^2$ is the background noise power.

In addition to AMC, without loss of generality, we adopt for the primary network the variable transmit power allocation algorithm proposed in [18]. This is an iterative power control algorithm that converges to a global optimum solution that maximizes the product of SINRs across all active links. In the algorithm, the transmit power at the $i$th primary link is updated in iteration $n + 1$ as,

$$P_{i}^{(p)}[n + 1] = \left(\sum_{j \neq i} G_{ij}^{(pp)} \sum_{m \neq j} G_{jm}^{(pp)} P_{m}^{(p)}[n] + \sigma^2\right)^{-1}$$

III. LEVERAGING ADAPTIVE MODULATION AND CODING IN UNDERLAY DSA

Before presenting our proposed underlay DSA technique, in this Section we outline the main ideas on how AMC can be leveraged to address the two main challenges associated with underlay DSA: How to establish the interference threshold in the PN and how SUs can autonomously become aware of the interference they create on the PN. As previously noted, AMC (or, as also called, link adaptation) has been used during the past two decades in practically all high-performance wireless communications standards and, as such, is assumed to be used in both the primary and secondary networks in this work. In this section we summarize some main features of AMC that are relevant to our fully autonomous and distributed underlay DSA scheme.

Fig. I obtained using the Matlab LTE Link Level Simulator from TU-Wien [30], shows the throughput versus signal-to-noise ratio (SNR) performance for the LTE system that will serve without loss of generality as the assumed AMC setup for the rest of this work (setup details for the simulation results shown in Fig. I are discussed in Section IV). In LTE, AMC consists of 15 different modes (each for a different “Channel Quality Indicator” - CQI) based on three possible modulation schemes which will be called “type 0” for QPSK (used for the smaller SNR regime), “type 1” for 16QAM (used
at intermediate SNRs), and “type 2” for 64QAM (used for the larger SNRs). In AMC, alongside the modulation order, channel coding rate is also adapted [31], [32]. Fig. 1 shows the throughput achieved for each AMC mode (each curve is labeled with the corresponding CQI value and AMC mode settings, formed by the modulation type and channel coding rate) and the overall performance curve of the AMC scheme, where the modulation type and code rate are chosen to maximize throughput but with a constraint on the block error rate (BLER) not to exceed 10%. During transmission, the transmitter chooses the AMC mode with maximum throughput at the estimated SNR of the link.

As was discussed in [18], the use of AMC in conjunction with transmit power control allows the background noise to increase up to a maximum value without significantly affecting the network average throughput. In the context of underlay DSA, this maximum noise value can be interpreted as the maximum value for the combined powers of background noise and interference from the SN and the rest of the PN. To see this important point in detail, consider Fig. 2 which is an expanded version of Fig. 5 in [18], now for different network loads ($N_P/N_{PBS}$) when using the LTE AMC setup just described and the power control algorithm from [18]. The figure shows the average throughput achieved in the PN by itself (the presence of an SN is not included in this result) as the background noise power increases. On the top, the figure shows the property associated with the use of adaptive modulation that for all network loads the average throughput remains approximately constant until noise power becomes sufficiently significant. This is not a trivial observation as networks with a higher load are operating in a regime more influenced by the interference rather the noise, but it is clear from the results that adaptive modulation manages to maintain a balance between interference and noise-dominated operation. The bottom of Fig. 2 shows as a function of noise power, the change in throughput relative to the throughput at the lowest noise power. The result exposes the remarkable property that the interference that would be imposed by the SN, which can be considered as background noise by a PN that is unaware of the presence of another network, will not significantly affect the average throughput in the primary network as long as the combined SN interference, imposed interference by other primary links and background noise remains below a threshold approximately equal to -85 dBm (although this number somewhat depends on the network load). Moreover, average throughput starts to decrease at approximately the same value of noise power for all network loads (around -90 dBm). This is a consequence of the link adaptation performed through AMC. Moreover, throughput relatively decreases faster with smaller network loads. We believe that this is because at smaller network loads, interference across the network is lower and a larger ratio of transmissions use the less resilient higher rate modulation types.

While AMC entails the adaptation of both modulation order and channel coding rate, it can be seen in Fig. 1 that the modulation order provides a coarse adaptation and that the channel coding rate enables a finer adaptation within each of the choices for modulation order. Moreover, an important difference between modulation order and channel coding rate adaptations is that while it is possible...
for a passive “listener” of the AMC transmission to infer the modulation order through the use of modulation classification signal processing, it is not possible to infer the channel coding rate. Indeed, there exists a large body of research in the area of modulation classification with some representative works briefly discussed in Sect. [1] (e.g. [15]–[17]). At the same time, the only known techniques to learn the channel coding rate in a primary link are not based on a passive listener but, instead, rely on the sharing of information between the PN and the SN through the SUs accessing the control feedback channel in the PN, [7], [10]. However, at will be seen, our proposed technique is able to overcome this limitation of inferring the channel coding rate without exchange of information between the PN and the SN.

We finally highlight that, as can be seen in Fig. 1, when the noise power increases (or equivalently the SN interference increases) the effect of AMC operation will be to change the AMC mode to one associated with a smaller CQI. At the same time, the modulation scheme with the smallest order is used for the smallest operating SINRs (because the transmission of less bits per symbol is more resilient to interference and noise). As the interference from secondary transmissions increases, primary links that are already using this modulation scheme in the absence of secondary transmissions will not switch to other modulation schemes because there is no other modulation scheme with fewer bits per symbols (with smallest associated CQI) to switch to. This means that transmissions from an SU that otherwise would generate a change in modulation scheme would not result in any change when the nearest primary link is already transmitting with the modulation scheme with smallest bits per symbol.

IV. AUTONOMOUS AND DISTRIBUTED UNDERLAY DSA FOR COGNITIVE RADIO NETWORKS

We now present the main contribution of this paper: a fully autonomous and distributed underlay DSA technique for a secondary CR network. We assume that the transmitting SUs are randomly located within the area covered by the primary network and that each of them has assigned a receiving SU randomly located within a circular region around the transmitter. The operation of the secondary network is fully autonomous and ad-hoc. This means that SUs do not rely on any exchange of information with the primary network and with other SUs (other than between transmitter-receiver pairs) and that the transmission control algorithm in the secondary network needs to be distributed. While there is no information exchanged between primary and secondary networks, it is assumed that the secondary network has knowledge of the underlying timing operation in the primary network so as to allow CRs to sense at appropriate times.

Fully autonomous operation implies that the primary and secondary networks operate as being unaware of the other (except for the above mild timing assumption), considering the other network transmissions as out-of-network interference akin to background noise. Then, when adding an underlay secondary network, the SINR in the \( i \)-th primary network link now becomes,

\[
\gamma_i^{(p)} = \frac{G_i^{(pp)} P_i^{(p)}}{\sum_{j \neq i} G_{ij}^{(pp)} P_j^{(p)} + \sum_{j=1}^{N_S} G_{ij}^{(ps)} P_j^{(s)} + \sigma^2}, \tag{3}
\]

where \( P_j^{(s)} \) is the transmit power from the \( j \)-th transmitting SU and \( G_{ij}^{(ps)} \) is the path gain from a transmitting SU \( j \) to a PU \( i \). Likewise, it is assumed that transmissions on the secondary network also make use of AMC, which is configured for each link based on its SINR. At the receiver for the \( i \)-th secondary network link the SINR, \( \gamma_i^{(s)} \), is

\[
\gamma_i^{(s)} = \frac{G_i^{(ss)} P_i^{(s)}}{\sum_{j \neq i} G_{ij}^{(ss)} P_j^{(s)} + \sum_{j=1}^{N_S} G_{ij}^{(sp)} P_j^{(p)} + \sigma^2}, \tag{4}
\]

where \( G_{ij}^{(ss)} \) is the path gain from the transmitter in the \( j \)-th secondary link to the receiver in the \( i \)-th secondary link, and \( G_{ij}^{(sp)} \) is the path gain from \( j \)-th BS to \( i \)-th SU. All transmissions are assumed to be over a flat quasi-static fading channel that is considered constant during a sensing and transmission period. This setup assumed for the secondary network is general, yet practical, as it is applicable to numerous wireless cognitive ad-hoc networks scenarios.

In the proposed underlay DSA technique, a cognitive engine at each SN transmitter learns the functional model of the interaction between the secondary and primary networks. Often, analytical models have been used to
characterize the performance of the secondary network. For example, in [33] the BER performance of different modulation orders have been characterized using analytical models. However, there are a number of shortcomings associated with resorting to analytical models, the major one being that every time a new component is added to the system, a new analytical model needs to be derived off-line and loaded into the system, while a CR is expected to be configurable and generalizable for unknown combinations of the input. Black-box modeling is an alternative approach to analytical models which consider analyzing the relation between input and output of a system and aims at building a predictor to estimate output values for unforeseen inputs and variations of the system configurations. In this work we will follow a black-box modeling approach.

Neural Networks (NNs) applied to black-box modeling have become increasingly popular as general purpose function approximators and, specifically, for dynamic system modeling [34]. Neural networks have been successfully applied to a number of modeling and time series prediction tasks. Due to the inherent capability of neural networks in modeling nonlinear systems and their higher robustness to noise, they frequently outperform standard linear techniques when the time series is noisy and the dynamical system that generated the time series is nonlinear [35]. The effect of SUs transmissions on the primary network is an example of a dynamic system and, in addition, throughput in the PU can be seen as a time series with a temporal dependency. In the case of one-step-ahead time series prediction tasks, only the estimation of the next sample value of a time series is required, without feeding back the output to the model’s input regressor. In other words, the input regressor contains only actual sample points of the time series. While considering multi-step-ahead or long-term prediction, the neural network model’s output should be fed back to the input regressor for a finite number of time steps [36]. In this case, the components of the input regressor, previously composed of actual sample points of the time series, are gradually replaced by previously predicted values. As a result, the multi-step-ahead prediction task is converted to a dynamic modeling task. In this case, the neural network model behaves as an autonomous system and tries to recursively emulate the dynamic behavior of the system that generated the nonlinear time series [37]. Compared to the one-step-ahead prediction, multi-step-ahead prediction and dynamic modeling are much more complex to deal with. However, neural networks models and, in particular recurrent neural architectures, play an important role in dealing with these complex tasks [38]. Elman introduced in [39] a class of recurrent neural models called simple recurrent networks (SRNs) which are essentially feedforward in the signal-flow structure with a few local and/or global feedback loops. Time delay neural network (TDNN) which is an adapted version of feedforward multilayer perceptron (MLP)-like networks with an input tapped-delay line can be used to process time series [38]. In the case of long-term predictions, a feedforward TDNN model will eventually behave similarly to the SRN architecture, since a global loop is needed to feed back the current estimated value into the input regressor. Temporal gradient based variants of the backpropagation algorithm is usually used to train the aforementioned recurrent neural networks – [40]. Regarding learning of systems with a long time temporal dependencies in their input-output signals, however, the learning tasks using gradient-based learning algorithms can be quite difficult [41]. In [42], the authors claimed that such learning tasks is more effective in a class of simple recurrent network model called Nonlinear Autoregressive with eXogenous input (NARX) [43] than in simple MLP-based recurrent models. This occurs in part because the NARX model’s input vector is cleverly built through two tapped-delay lines: one sliding over the input signal and the other sliding over the network’s output.

\[ y(n+1) = f\left( y(n), y(n-1), \ldots, y(n-d_y); \\ u_1(n), u_1(n-1), \ldots, u_1(n-d_{u_1}); \\ u_2(n), u_2(n-1), \ldots, u_2(n-d_{u_2}) \right) \]

where \( u(n) \) and \( y(n) \) denote, respectively, the input and output of the model at discrete time step \( n \), and \( d_{u_1} \geq 1, d_{u_2} \geq 1 \) and \( d_{y} \geq 1, d_{u_1} \geq d_y, d_{u_2} \geq d_y \) are the input-memory and output-memory orders, respectively. The nonlinear mapping \( f(\cdot) \) in (5) is generally unknown and can be approximated, for example, by a standard feedforward multilayer neural network. If the non-linear mapping can be learned accurately by a neural network of

Fig. 3. NARX network with two delayed inputs and one delayed output.
moderate size (measured in terms of number of layers and number of artificial neurons in each layer), the resource allocation based on the output of the NARX neural network can be done in real time, since passing the input through the neural network only requires a small number of simple operations. In Fig. 3 each circle represents an “artificial neuron”, an elementary operation unit in the NARX neural network model which performs an operation on its inputs given by,

\[ z = \phi \left( \sum_i w_i x_i + b \right), \tag{6} \]

where \( z \) is the output of the neuron, \( x_i \) is the \( i \)th input, which is multiplied by the weighting factor \( w_i \), \( b \) is a bias applied to the neuron (not explicitly shown in Fig. 3) and \( \phi(\cdot) \) is called the “activation function”. This activation function \( \phi(\cdot) \) for the hidden layer is a tangent sigmoid while the activation function used for the output layer is linear (the input layer is not truly formed by artificial neurons but rather it is conventionally included as a representation of the connections of inputs into the neural network).

In this paper, the architectural approach proposed for modeling nonlinear systems was chosen based upon the NARX neural network structure [43]. Specifically, we choose the NARX neural network to implement the cognitive engine in a CR. Fig. 4 illustrates the block diagram of an SU with its cognitive engine based on the NARX neural network, as well as other processing steps for the inputs and output of the neural network. The function of this cognitive engine will be to aid in the setting of power control and AMC parameters for a transmitting SU, by predicting for different transmit settings the throughput \( \hat{T} \) (equivalently the CQI or AMC mode) of the nearest PN link. Under our imposed practical condition of no exchange of information between the primary and secondary networks, a CR can only estimate the modulation order, after performing modulation classification signal processing on the PN transmissions, and immediately has no direct way to know the coding rate in use (this is, unless accessing the PN’s feedback channel, which would violate our condition). Moreover, practical limitations further dictate that the modulation classification can only be performed on the one primary transmission that it is being received with strongest power (usually this is the closest one), making the other transmissions be interference. It is assumed that the estimation of modulation type does not rely on the SU accessing any information from the PN feedback channel and is error free using any of the methods existing in the literature (e.g. [16] or [17]). Since the modulation order setting of a primary link provides a coarse indication of its SINR, this is, of the effect that a SU transmission at some power level has on the primary link, we configure the NARX neural network cognitive engine to have as inputs the most recent values of assigned transmit power levels at the SU \( u_1(n) \) and, corresponding to these transmit power levels, the inferred modulation order \( u_2(n) \) being used in the closest primary link. The output of the NARX neural network cognitive engine is the predicted throughput (i.e. \( y(n) \) in Fig. 3) corresponds to \( \hat{T}(n) \) in Fig. 4) at the primary link closest to the transmitting CR (which corresponds to a choice of AMC mode). As shown in Fig. 3 a chain of unit-delay blocks creates a sequence of prior inputs and corresponding outputs as further input to the neural network.

The proposed NARX neural network undergoes a training process to determine the values of the weights and biases for the artificial neurons. In this training process, the weight and bias values are updated according to the Levenberg-Marquardt optimization method. This method involves a back-propagation algorithm to compute the gradients [45] of the prediction error corresponding to the artificial neurons. It is known that in the case of function approximation problems, for the neural networks containing up to a few hundred weights, the Levenberg-Marquardt algorithm will have the fastest convergence [46]. Mean square error (MSE) was chosen as the prediction error metric:

\[ MSE = \frac{1}{N} \sum_{i=1}^{N} (e_i)^2 = \frac{1}{N} \sum_{i=1}^{N} (T_i - \hat{T}_i)^2, \tag{7} \]

where \( N \) is the number of neurons in the hidden layer, \( T_i \) and \( \hat{T}_i \) are target and predicted values, respectively. In test cases, different number of neurons in the hidden layer as well as time delay steps were evaluated. The best performed structure was found to be with 50 hidden nodes and 7 time delay steps. Fig. 5 illustrates the performance of the NARX neural network for a primary network load equal to 0.64. Further details regarding the generation of the target prediction values \( T_i \) used during training are provided in the next Section.

For the complete system operation, first the SUs avoid transmission while the PN initially adjusts its power and AMC parameters using the iterative power control algorithm [3]. During this stage, the SUs listen to the PN transmission and infer the modulation order used by their closest primary link. At this stage, the SUs obtain an estimate of the modulation order used by their corresponding nearest primary link when the SN is not transmitting. After this, each SU proceeds to send a series of short probe messages configured with different transmit powers. Each SU performs modulation classification for each probe message on its nearest primary link. The sequence of probe message transmit powers and ensuing modulation orders are fed to the NARX neural network, which provides the sequence of corresponding estimated throughput values at the nearest primary link, \( \hat{T} \). Note that this sequence of estimated throughput values includes the
one with no transmissions from the SN. Since estimating the throughput is equivalent to estimating the CQI and the corresponding AMC mode, the NARX neural network is able to provide an estimate of the nearest primary link SINR with a finer resolution than what could be derived from the modulation classification alone that is present at its input. Furthermore, the SU can use the sequence of estimated throughput values to infer what would be the effect of its transmission on the nearest primary link by comparing the change in throughput value against that without the SN transmission. As seen in Fig. 4, the SU uses this information to find its own transmission parameters. We will consider two approaches for the SUs to choose transmit settings. In the first one, the SU chooses the maximum transmit power value that is estimated to not lead to a change in modulation order at its nearest primary link. In the second approach, the SU chooses the maximum transmit power value that is estimated to not change the nearest primary link throughput beyond a maximum relative change value. Note that the second approach differs from the first one in that it fully uses the advantage provided by the NARX neural network in providing the finer resolution inference on the nearest primary link full AMC mode, instead of the coarser inference on modulation order that the first scheme is based on. Additionally, for both approaches, those SUs that estimate that their closest primary link is transmitting in the lowest rate AMC mode when the SN is not transmitting (because of already experiencing a very low SINR, likely leaving no room for added interference from the SN) are prevented from transmitting. This guarantees that the reduction in the average rate of the primary link experiencing the poorest channel quality (CQI equal to 1) is minimized.

Going back to Fig. 4 helps to gain an intuition into the NARX neural network cognitive engine operation. The NARX neural network receives as one input the possible SU’s transmit power levels organized in sequence and, as another input, the corresponding modulation order sensed from the nearest primary link. During training, the NARX neural network learns to predict the throughput values at the nearest primary link that correspond to the two input sequences. Considering Fig. 5, we can think that the sequence of transmit power values that is input to the NARX neural network will yield a range of interference values, which will correspond to a “segment” of SINR values in the abscissa of Fig. 1. The position of this segment within the range of SINR values depends on the many factors reflected in (3) (e.g. primary channel gain, interference from other SUs, etc.) but the NARX neural network has a sense of where the segment is thanks to the reference provided by the sequence of modulation orders at the input (e.g. if for the setup in Fig. 1 the sequence of modulation schemes are QPSK and 16QAM, the SINR segment is around 10 dB). During training, the NARX neural network is presented with multiple different such segments from different wireless environment scenarios, eventually learning the throughput vs. SINR AMC performance curve. During operation of the NARX neural network (the testing phase), sensing the sequence of modulation schemes that results from probing SU transmissions with a sequence of possible power settings allows the NARX neural network to localize the segment of SINR values for the nearest primary link (in effect, finding the network scenario presented during training that best matches the existing wireless environment) and, consequently, predicts the corresponding throughput from the AMC performance curve.

V. SIMULATION RESULTS

The performance of the presented technique was evaluated through Monte Carlo simulations (150 runs) based on a PN “playground” consisting of a five-by-five BSs grid \( N_{PBS} = 25 \) with neighboring base stations separated by a distance of 200 m. To avoid edge effects in the play-
ground, the grid wraps around all its edges. One channel was singled out in the experiment and any of the base stations can have this channel active. In order to reflect realistic AMC settings, we assumed that all transmissions are based on an LTE 2x2 MIMO configuration and that the channel of interest is one resource block with a bandwidth of 180 kHz.

As noted earlier, we assumed that there are $N_P$ active base stations that are using the same channel to communicate with their respectively assigned PU receivers. The location of the $N_P$ PU receivers is determined at random using a uniform distribution with the limitation that no base station could have more than one receiver assigned to it. Also, the receivers were connected to the base station from which they received the strongest signal. Transmit powers in the primary network were limited to the range between -20 and 40 dBm. The transmit power assignment for the $i$th active primary link ($i = 1, 2, \ldots, N_P$) follows the same algorithm as in (2). Each primary transmission considers the other network transmissions as out of network interference akin to background noise.

In the simulation, the SN consisted of $N_S = 4$ transmit-receive pairs of CRs, with the transmitters placed at random (also with a uniform distribution) on the PN playground, around their respectively assigned transmitter within a distance not exceeding 50 m. In the simulation setup we intended to reflect a situation where the PN had somewhat more capabilities (achieving larger throughput and communication range) than the SN because of being the incumbent to the spectrum band under consideration. Therefore, we assumed that the SUs were smaller devices that communicated with a single omni-directional antenna with transmit power in the range of -30 to 20 dBm. Twenty equally spaced power levels in this range are considered as the set of allowed settings for transmission. The operation of the secondary network, as mentioned before, is fully autonomous and ad-hoc and the transmission control algorithm is distributed. It is also assumed that the secondary network has knowledge of the underlying timing operation in the primary network so as to allow CRs to sense and transmit at appropriate times.

All links assumed a path loss model given by $L = 128.1 + 37.6 \log d + 10 + S$ (in dBs), where $d$ is the distance between transmitter and receiver in km, $S$ is the shadowing loss (modeled as a zero-mean Gaussian random variable with 6 dB standard deviation) and the penetration loss is fixed at 10 dB.\cite{47}. Noise power level was set at -130 dBm. It should be noted that all transmissions adopt AMC to adapt their transmission to the quality of their respective link.

Each neural network was trained/validated with a data set of 4000 samples collected from a network simulation with the setup just described. A subset of the data set (2800 samples or 70% of the data set) was used to train the neural network and to present the CRs with new environmental conditions, the rest of data was used to compare the prediction performed by the trained neural network with the actual expected performance in order to encounter new environment conditions. In order to generate training data for the neural network cognitive engine, a comparable SN was devised that maintained the ability to use the estimated modulation order of the nearest primary link but without the cognitive engine shown in Fig. 3. Instead, this comparable system implemented a distributed power control algorithm modified to incorporate the modulation order of the nearest primary link. A number of algorithms had been proposed for distributed power control in ad-hoc wireless network. One of the first ones, and the precursor to many related variants, is the Foschini-Miljanic algorithm,\cite{43}, which implements an iterative distributed power control process so as to meet a target SINR. We adopted this iterative power allocation algorithm for the alternative SN that generated the data set to train the NARX-NN cognitive engine at each SU. Specifically, power is calculated for a secondary link $i$ at each iteration $m$ using the update formula,

$$P_i^s[m + 1] = \left( \frac{\beta_i}{\gamma_i^s[m]} \right) P_i^s[m], \quad (8)$$

where $P_i^s$ is the transmit power, $\beta_i$ is the target SINR and $\gamma_i^s[m]$ is the actual SINR measured in the $m$th iteration which can be calculated through (4). The fact that this algorithm associates power control with a target SINR is a useful feature in our case because the target SINR, when met, also determines the modulation order to be used as follows\cite{18},

$$T_i^{(s)} = \log_2(1 + k \gamma_i^{(s)}), \quad i = 1, 2, \ldots, N_S. \quad (9)$$

Consequently, we can think that instead of having a set of possible [modulation, channel code] pairs, now we have a set of target SINRs to choose from. Let $\mathcal{B} = \{b_1, b_2, \ldots, b_K\}$ be this set, where target SINRs $b_i$’s are assumed to be sorted in ascending order. Of course, reducing the target SINR will result in decreasing the transmit power. As a consequence, the algorithm provides the mechanisms to both adapt transmit power and AMC settings in a distributed way. Moreover, for fair comparison to the system with the proposed NARX neural network cognitive engine, the transmit power from SUs also needs to be constrained by the goal to not degrade the SINR of the closest primary network link to the extent of reducing the modulation order (not having the NARX neural network, this competing SN cannot operate based on the use of throughput inferred for the nearest primary link and can only make use of the modulation order estimated from the modulation classification process). Modifying the Foschini-Miljanic algorithm by reducing the target SINR allows to manage this constraint by resulting in a reduction in the SU
transmit power. As such, we adopted for the control of CR transmissions in the alternative SN this modified version of the Foschini-Miljanic algorithm, where the SU target SINR is progressively reduced until there is no change in the modulation order of the nearest primary link. We note here that while it is certainly possible to use one of the many existing enhancements to the Foschini-Miljanic algorithm, we chose to use the original version without improvements because its provides a baseline performance measure and because this power control algorithm or a variation of it are not the contribution of our work. Of course, the PUs in this system maintained the power allocation algorithm proposed in [18], as explained in Sect. [I] Moreover, note that in AMC the modulation order transmitting the smallest number of bits per symbol is used for the smallest operating SINRs (because it is more resilient to interference and noise). When the interference from the SN increases, the primary links that were already using the smallest possible modulation orders will not switch to other modulation orders because there is simply no other modulation order with fewer bits per symbols to switch to. This means that transmissions from an SU that otherwise would generate a change in modulation order would not result in any change when the nearest primary link is already transmitting with the modulation order with smallest bits per symbol. Moreover, primary links using this modulation order, do so because their SINR is at the lower range of the operating SINRs, which imply that they are at a link state that likely may not leave much room for added interference from SUs. Because of these reasons, and in the interest of prioritizing the protection of primary links against excessive SN interference, we configured the alternative SN so that a CR will not transmit if it senses that its nearest primary link is using the lowest modulation order when the SN is not transmitting (as explained in Sect. [IV] our proposed technique implements a mechanisms with the same spirit but based on checking for the smallest CQI at the nearest primary link when the SN is not transmitting, instead of smallest modulation order).

Figs. 6 through 8 study the throughput performance in the primary and secondary networks for our presented technique and contrast them against other schemes. As indicated in Sect. [IV] for the presented technique we considered two approaches for the SUs to choose transmit settings. The first approach, labeled in the figures as “PN+SN- NN Cog. Eng.- Modulation”, makes a limited use of the cognitive engine capabilities by making the SU choose the maximum transmit power value that is estimated to maintain unchanged the modulation order (but not necessarily the channel coding rate) at its nearest primary link. The second approach makes full use of the cognitive engine’s throughput estimation capabilities at the nearest primary link, by making the SU choose the maximum transmit power value that is estimated to not change the nearest primary link throughput beyond a maximum relative change value. This approach is itself divided into a case where one probe message is sent for each possible power setting (for a total of twenty probe messages) and a second case that explores a reduction in the overhead from transmitting probe messages which transmits just seven messages and uses interpolation to complete the information for the rest of available transmit power settings. Still, both of these cases evaluate the advantage in being able to estimate and use the full AMC mode, as opposed to only the modulation order which is the configuration for the aforementioned “PN+SN- NN Cog. Eng.- Modulation” system. To show how our technique is able to leverage the estimation of the full AMC mode and provide each SU with a fine control over the interference it imposes to the nearest primary transmission link, we obtained results for three different limits on relative average throughput change in the PN: 2%, 5% and 10%. In the figures, we labeled the results for the first case (sending all probe messages) as “PN+SN- NN Cog. Eng.- 2%- All probe messages” for a limit on relative average throughput change in the PN of 2%, “PN+SN- NN Cog. Eng.- 5%- All probe messages” for a limit on relative average throughput change in the PN of 5%, and “PN+SN- NN Cog. Eng.- 10%- All probe messages” for a limit on relative average throughput change in the PN of 10%. Similarly, for the second case (seven probe messages), the labels for 2%, 5% and 10% limit on relative average throughput change in the PN are “PN+SN- NN Cog. Eng.- 2%- Seven probe messages”, “PN+SN- NN Cog. Eng.- 5%- Seven probe messages” and “PN+SN- NN Cog. Eng.- 10%- Seven probe messages”, respectively. The performance of these realizations of the proposed underlay DSA technique is compared in the figures against other schemes. The first such contrasting scheme, labeled in the figures as “PN+SN- Adapted Foschini-Miljanic”, is the same system used to collect training data and described in the paragraph preceding this one. This scheme incorporates one of the main contributions of this work (i.e. the use of modulation classification on AMC to infer the conditions of the nearest primary link) but it lacks the NARX neural network cognitive engine’s capability to predict the full AMC mode at the nearest primary link. In addition, we considered two schemes that select transmit power for the SUs based on an exhaustive search across all possible setting permutations. In contradiction with our goal to avoid any exchange of information between the primary and secondary networks, these two schemes also incorporate the ability to perfectly know the CQI on the primary links as if the SN had access to the control feedback channels in the PN, akin to the approaches from [7]. [10]. The first exhaustive search scheme, labeled “PN+SN- Exh.
search-Max PU throughput”, finds across all possible SUs transmit power permutations, the setting that results in no change in modulation order at any primary link and maximum average throughput in the PN. The second exhaustive search scheme, labeled “PN+SN- Exh. search-Min PU throughput”, favors the average throughput at the SN by finding across all possible SUs transmit power permutations, the setting that results in no change in modulation order at any primary link and minimum average throughput in the PN. Clearly, the two exhaustive search curves present extreme performance results based on ideal setups. Finally, Fig. 6 includes a curve, “PN without SN”, which shows the average throughput achieved by the PN when the SN is not present.

Fig. 6. Average throughput in primary network.

Fig. 6 shows the average throughput achieved for the PN as a function of the PN load, $N_P/N_{PBS}$, while Fig. 7 shows the change in this throughput relative to the “PN without SN” case. It can be seen in both figures that the use of the proposed NARX neural network cognitive engine results in SUs transmit settings that reduces the average throughput in the PN much less than the case when the modified Foschini-Miljanic algorithm is used in the SU. Moreover, in the figures, the “PN+SN- Exh. search-Min PU throughput” curve illustrates the extent to which the average throughput in the PN can be affected without changing the modulation order at the nearest primary links (as much as 19%). This indicates that considering only the modulation order provides an initial means for implementing a fully autonomous underlay DSA but with the limitations associated with the coarse indication of the primary links SINR given only by the modulation order. The “PN+SN- Adapted Foschini-Miljanic” and the “PN+SN- NN Cog. Eng.- Modulation” schemes result in relative reduction in the PN average throughput by as much as 15.5% and 14.5%, respectively. The best performance in terms of controlling the effect of SN transmissions on the PN is achieved with our proposed scheme using the full inference on the primary links’ full AMC mode (in actuality, the throughput) provided by the NARX neural network cognitive engine. This is seen through the results obtained for the two cases (transmitting either all or seven probe messages) designed based on a limiting maximum relative change in average throughput at the nearest primary link, for which we show results for 2%, 5% and 10% relative change limit. Moreover, these schemes include the means to control as desired the level of SN effect on the PN (by setting the limit maximum relative change). In fact, the “PN+SN- NN Cog. Eng.- 2%-All probe messages” along with “PN+SN- NN Cog. Eng.- 2%- Seven probe messages” curves exemplify the very fine level of control that is possible to achieve with the proposed approach. Fig. 7 shows a small difference in terms of the target maximum relative change in average PN throughput and the actual achieved relative change in PN throughput (maximum 2.5% instead of 2%, 6% instead of 5% and 11% instead of 10% in case of utilizing all probe messages). This difference is attributed to errors in estimating the throughput at the PN, which are discussed more in detail later in this Section (see discussion for Fig. 10). We note that these differences can only be seen at the smallest PN network load of 0.16, which is due to the larger sensitivity of the relative change in PN average throughput with lower PN load as was
previously highlighted for Fig. 2. It can be also seen that the scheme where a fraction of probe messages is used yields significant reduction in the transmission overhead of probe messages (roughly a threefold reduction) without much sacrifice in performance (maximum 3.5% instead of 2% actual achieved relative change in PN throughput compared to 2.5% maximum change with all the probe messages). Finally, the curve “PN+SN- Exh. search-Max PU throughput” coincides with the “PN without SN” curve as the exhaustive search solution that maximizes average PN throughput is essentially the one with no transmissions in the SN (with one caveat to be discussed in Fig. 8).

Considering Fig. 7 in the context of the bottom plot of Fig. 2 we can see that the relative throughput change in the PN when using our proposed technique corresponds to points at equivalent background noise power between -96 and -85 dBm (depending on the target maximum PN relative throughput change setting) just to the left of the “elbow” of the curves in Fig. 2. This result confirms that our proposed technique succeeds in its main goal of autonomously and distributively determining the transmit power of the SUs such that the interference they create remains below the maximum threshold value associated with the background noise power levels that a PN with adaptive modulation can sustain. At the same time, the proximity of the equivalent background noise levels generated by the SN to the “elbow” of the curves in Fig. 2 indicates that our proposed algorithm is able to find transmit settings for the SUs that will result in as large SN throughput as could be allowed by the PN interference limit.

Fig. 8 shows the average throughput achieved in the SN as a function of the PN load. Naturally, the more a scheme affects the PN throughput, the larger the SN throughput it could achieve. As such, it can be seen that our approach based on a limit maximum PN relative throughput change not only provides the means to control how much the PN is affected by the SN, but also it allows to control how large the average throughput at the SN is desired to be (at the expense of the PN). Even so, the realization with the more restrictive setting for the SN (the one with a maximum PN relative throughput change of 2%) still achieves useful average throughput values between 132 and 50 kbps for a channel with 180 kHz bandwidth (in case of transmitting seven probe messages the average throughput at the SN is slightly larger which coincides with the results in Fig. 7). Also, note that at low PN loads, the “PN+SN- Exh. search-Max PU throughput” system shows throughput values that imply transmission in the SN. This does not contradict our earlier statement that this result essentially coincides with the “PN without SN” case. Instead, the transmissions in the SN that are seen in this case correspond to infrequent setups where the SUs are located so far away from the few active primary links (consider that this effect occurs only at very low PN loads) that they can transmit with very low power with no practical effect on the PN.

Fig. 9 shows the cumulative distribution function (CDF) of the throughput in SN for different primary network load. This figure presents a perspective that explains an added advantage of the NARX neural network solution compared to the modified Foschini-Miljanic algorithm-based solution. The figure shows that in the case of the SN that uses the modified Foschini-Miljanic algorithm, around 15% of the time SUs will be unable to transmit (throughput is zero) when the PN load equals 0.16 and this number increases to around 30% as the PN load increases. This is because the SN that uses the Foschini-Miljanic algorithm is only able to infer the modulation scheme used in the primary link and not the channel coding rate, which leads to SUs not being able to have a finer assessment of their effect on the PN when the nearest primary link is using a modulation “type 0”. As a result, and as discussed earlier, in order to protect the PN, those SUs using the modified Foschini-Miljanic scheme for which the nearest primary link use modulation “type 0” are blocked from transmitting. In contrast, the proposed technique using NARX neural network, “Pn+SN-NN Cog. Eng.- Modulation”, is able to estimate the finer AMC configuration of coding rate setting, making this protection and the blocking of SU unnecessary (except when the nearest link is using the AMC mode for a lowest rate, which corresponds to CQI=1). Consequently, as seen in Fig. 9, the proposed technique increases the transmission opportunities in the secondary network by the same percentage of time that the SUs are blocked in the case of using the modified Foschini-Miljanic algorithm-based solution.
Fig. 9. Cumulative distribution function (CDF) of the throughput in the secondary network.

As just seen, a key advantage of the proposed technique follows from the remarkable ability to estimate the channel coding rate used in a primary link. Therefore, we evaluated the performance of NARX neural network in estimating the CQI in a primary link (which is equivalent to the full AMC mode consisting of modulation order and channel coding rate). Fig. 10 shows as a function of the primary network load the relative frequency of the absolute error when predicting the CQI for the case of transmitting all probe messages. This Figure shows that as the network load increases, the probability of an accurate estimation (prediction absolute error equal to zero) increases and reaches more than 80% for a load equal to 0.48. The Figure shows that, overall, the probability of significant errors when predicting CQI is quite small but, nevertheless, we speculate this to be a factor in the (still small) reduction in PN average throughput and in the small difference at low PN loads between the target maximum relative change in average PN throughput and the actual achieved relative change in PN throughput for our schemes based on target maximum PN relative throughput change.

VI. CONCLUSION

In this paper we have presented a fully autonomous and distributed underlay dynamic spectrum access technique that is based on a NARX neural network cognitive engine. The NARX neural network engine leverages the use of adaptive modulation and coding in the primary network to infer the effect that different settings in a secondary network transmission would have on the primary network. In effect, the NARX neural network learns to use the sensed modulation used in the nearest primary link to predict the throughput (equivalently the chosen modulation scheme and the channel coding rate) resulting from a secondary link transmission setting in the same primary link. Based on this NARX neural network capability, we presented two variants for the proposed underlay dynamic spectrum access mechanism: one where the secondary users choose the maximum transmit power value that is estimated to not lead to a change in modulation order at their respective nearest primary link, and another where the secondary users choose the maximum transmit power value that is estimated to not change their respective nearest primary link throughput beyond a chosen maximum relative change value. The performance of the latter proposed underlay dynamic spectrum access mechanism was examined for the cases of sending all or a third of all probe messages to infer the effect of SU transmission on the transmission of the nearest PU.

Fig. 10. CQI estimation performance of the NARX neural network.

Simulation results show that the proposed technique is able to accurately predict the modulation scheme and channel coding rate used in a primary link without the need to exchange information between the primary network and the secondary (e.g. access to feedback channels), resulting in the proposed technique succeeding in its main goal of determining the transmit power of the secondary users such that the interference they create remains below the maximum threshold that the primary network can sustain with minimal effect on the average throughput, along with reducing the transmission overhead in case of sending fraction of probe messages. Through simulation results, it was shown how the proposed underlay DSA is able to control its effect on the primary network with a very fine level of granularity. At the same time, it was seen that our proposed algorithm is able to find transmit settings for the secondary users that will result in as large throughput in the secondary network as could be allowed by the primary network interference limit. Specifically, it was seen that for the proposed system with a target primary network maximum relative average throughput change of 2%, the achieved relative change was less
than 2.5% when sending all probe messages, and only for a limited regime of PN loads, while at the same time achieving useful average throughput values in the secondary network between 132 and 50 kbps for a channel with 180 kHz bandwidth. When reducing three times the number of transmitted probe messages, the proposed scheme maintains the ability to finely control the effect on the primary network while exhibiting a minimal increase in the relative average throughput change at the primary network. Moreover, it was discussed how our proposed scheme based on a target primary network maximum relative average throughput change allows to manage the tradeoff between effect of the secondary network on the primary network and achievable throughput at the secondary network. Finally, we also discussed how the ability of our proposed technique to predict the full AMC mode (not just the modulation scheme) results in a significant increase in the transmission opportunities in the secondary network compared to schemes that only use the modulation classification information.

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