Learning Characterization Framework and Analysis for a Meta-Cognitive Radio Engine

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***Abstract*—Cognitive radio engine (CE) designers are continuously working to understand and develop better learning techniques to be employed within their designs. Each of these algorithms has its strengths and deficiencies depending on the application scenario. Distinguishing when each learning technique should be used is a complex and time-consuming task and currently CEs do not have this ability. The main objective of this paper is to demonstrate that a CE with meta-abilities can choose the learning technique that is best suited for each application scenario. We first characterize different wireless scenarios (e.g., high/low SNR, available bandwidth, and primary user activity) and performance of each CE technique. By using these characterizations, we are able to evaluate the effectiveness of each learning technique in terms of the characterized scenario. By enabling the meta-CE to evaluate each learning technique, it also paves the way for equipping the meta-CE with the techniques needed to develop and evaluate new learning techniques that can be used during the meta-CE's operation. Our results show that when we use meta-CE techniques, the CR achieves the highest performance rate 92.5 % of the time. This is because, the meta-CE techniques compared with regular CE techniques provide higher adaptation abilities in different environments. Finally, we test three different learning techniques in 100 channel configurations from low to high SNR, we present the meta-CE work flow and evaluate the performance of the meta-CE. Furthermore, we demonstrate that a meta-CE learning technique can provide more efficient decisions than each individual CE learning techniques.**

I. Introduction

Cognitive radio (CR) is an active research area in wireless communications for more than a decade. CRs have advanced adaptation capabilities, which are facilitated using artificial intelligence (AI) techniques [1]. Generally, a CR is an intelligent system that adapts its internal operation parameters (e.g., transmit-power, modulation, coding, etc.) by observing and learning its surrounding environment to achieve more reliable communication links and efficient utilization of the radio spectrum [2]. The intelligence techniques of a CR are implemented in an agent [3] commonly referred to as a cognitive engine (CE). The CE makes decisions based on its experience, observation and supervises its own performance. Figure 1 depicts a general form of a CE; the CE component will make decisions based on defined objective functions, sensed environment metrics, and past decision memory.

Throughout CR history, various types of CEs with different learning and optimization techniques were proposed. Each of them has its own advantages and disadvantages on how to maximize the radio's performance. Some perform really well in high SNR conditions; others are more effective in low SNR conditions. The goal of this paper is to introduce a meta-CE in order to maximize the effectiveness of all the learning techniques available to the meta-CE.

Meta-cognition is defined as "cognition about cognition", or "knowing about knowing" [4] It can take many forms; it includes knowledge about when and how to use particular strategies for learning or for problem solving. The theory of meta-cognition can play an effective role in cognitive radio due to its higher ability to maintain, adjust and supervise cognitive processes. Gadhiok *et al* [5] states "In contrast to a typical cognitive radio that operates with a fixed personality, the meta-cognition ability enables the radio to use knowledge about its cognitive processes and external environment to help direct the decision-making and learning process and arrive at the best solution". Meta CR is a radio that uses a CE with meta-abilities. Meta-abilities (Meta-cognitive skills) may be defined as an ability for controlling learning processes in a higher level; in this context, it means that a CE can control the individual CE techniques.

This paper makes three key contributions. First, we statistically estimate and evaluate the performance of three CE techniques based on the operating objective. We define our objective function with respect to the Packet Success Rate (PSR) of the transmitted data packets and the achieved throughput The PSR is easier to observe than bit error rate (BER) and its usage simplifies the design process. Using the PSR allows our design to be centered on only two numbers: the successes and failures at each set of channel conditions and configuration pair. After estimating each CE performance, we evaluate our CE techniques by comparing and analyzing the learning curves. A learning curve is a graphic representation of the relationship between learning and outcomes. The main idea of a learning curve is "The more you experiment, the better your outcomes will be, through learning" [6]. We create the learning curves for each of the CE techniques, then we will compare these learning curves in order to find out which of them meet our expectations in a defined time interval. We show that based on the channel conditions, the performance of the learning techniques significantly differs. That said, some techniques will reach the best communication method sooner than the others, in a time-limited time horizon, the advantage of each technique can be determined.

Second, we characterize various channel scenarios based on statistics of the available channels. The purpose of this characterization is to distinguish the performance of each CE technique and, more importantly, to get insights on the factors

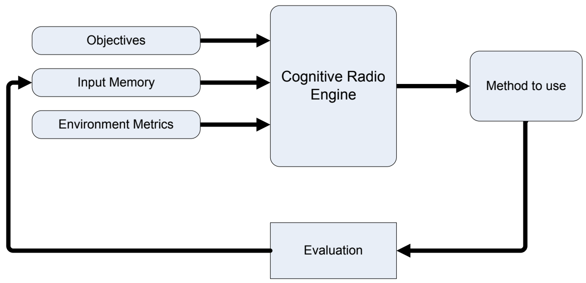

Fig. 1. General CE framework

that affect the performance of the CE techniques. For example, the performance of the CE techniques is significantly different in high SNR versus low SNR scenarios. Finally, by using statistical metrics of SNR and the eigen-spread of eigen values of the channel matrix, we are able to differentiate between channel scenarios based on CE techniques' performance under those scenarios.

Third, we propose a meta-CE based on nearest-neighbor classification, which plays a pivotal role in our framework. The m brain consists of several components that each of them has a specific purpose. One of these components senses the for estimating the metrics. Another one stores the reuslts of each CE technique's performance characterization. The meta-CE categorizes the performance characterization a reference library that is used for making future on similar cases. We test our meta-CE by using three individual CE techniques:ϵ-greedy exploration with two different parameters and the Gittins index strategy in 200 different channel scenarios, with 110 total available methods. The purpose of these tests is to evaluate the performance and accuracy of the meta-CE in various channel scenarios. We show that by using a meta-CE we are able to use the technique that is best suited for each channel scenario.

A. *Paper Organization*

This paper is organized as follows: In Section II, we provide an overview of CE design works. Section III, develops the learning curve approach for analyzing the CE techniques' performance. Furthermore, we introduce all the components of our meta-CE in detail. Moreover, we present the learning curve inferences for evaluating CE techniques utilization. Section IV, presents the results of a meta-CE with three CE techniques. Finally, the and conclusions are given in Section V.

II. Background

To make CR possible, communication engineers have, in the last few years, borrowed ideas from machine learning and AI [1]. A cognitive engine (CE) is an intelligent agent who enables the radio to have the desired learning and adaptation abilities. This intelligent agent [7] senses its environment (the wireless channel), acts by using a communication method based on its experience, and observes its own performance to learn its capabilities, adding to its experience base. The work of Rieser, Rondeau, and Le [8]–[10] propose a CE that deals with the user, policy, and radio domains. Their designs are similar and based on the Genetic Algorithm (GA), cased-based reasoning (CBR), and multi-objective optimization principles. He et al. [11] designed a CBR-based CE for IEEE 802.22 wireless regional area network (WRAN) applications and also investigated the radio and policy domains. Other works have focused only on the radio domain. For example, Newman et al. [12] and Z. Zhao, et al. [13] applied a GA and particle swarm optimization, respectively, to multi-channel radio links. On the other hand, N. Zhao et al. [14] proposed a CE design based on ant colony optimization. Zhang and Weng designed a CE with dynamic resource allocation [15], and Y. Zhao et al. [16] looked into utility function selection for streaming video with a CE testbed. Finally, for learning and optimization of a wireless link, Baldo and Zorzi [17] applied an artificial neural network (ANN) and Clancy et al. [18] used predicate logic.

CE design is only one aspect of CR; significant work has been done in other CR areas [19], mostly related to Dynamic Spectrum Access (DSA). For example, fundamental CR studies have been done on achievable rates [20], communication limits [21], fundamental issues [22], and design trade-offs [23]. Sridharan and Vishwanath [24] and Jafar and Shamai [25] derive theoretical capacities for multiple-input and multiple-output (MIMO) CR systems, and Scutari et al. [26] propose some techniques for operating in a MIMO spectrum-sharing setting. Work in other CR aspects includes spectrum sensing [27], [28], cognitive networks [29], [30], security [31], and minimization of system power consumption [32].

J. H. Flavell was the first to use the word "metacognition" [33]. According to Flavell refers to ones knowledge concerning one's own cognitive processes and products or anything related to them, e.g., the learning-relevant properties of information or data. For example, I am engaging in metacognition if I notice that I am having more trouble learning A than B; [or] if it strikes me that I should double check C before accepting it as fact." Along with metacognition, the metamemory term means understanding of onesknowledge state [34]. In our proposed meta-CE , there is a metamemory which stores informationaboutthe performance states of each CE technique and enables self-monitoring for the meta-CE's operations. self-awareness of memory has important implications on how the intelligent agent learns and uses memories [33].

A meta-CE decides based on the information that was gathered from the metamemory in form of learning curves. A learning curve is a graphical representation of performance during learning over time that is updated every time the task to be learned is repeated. The first person to describe the learning curve was Hermann Ebbinghaus in 1885 [35], in the field of the psychology of learning.

In conclusion, a meta-CE chooses the best of the available CE techniques based on the channel metrics and in turn the chosen CE techninue selects the communication method, which is the set of all the applicable parameters that characterize the radio transmission and is part of the decision process. The parameters may include channel coding, modulation, pulse shaping, multi-antenna method, radio channel, bandwidth, etc. This paper provides the building blocks (methods) towards a metacognitive agent and CE framework as shown in Figure 2.

Gadhiok *et al* [5] propose a meta-CE, which has two CEs, one based on CBR and one on GA. The meta-CE switches between these engines using a threshold level based on the available time horizon. As a result, the GE CE which takes

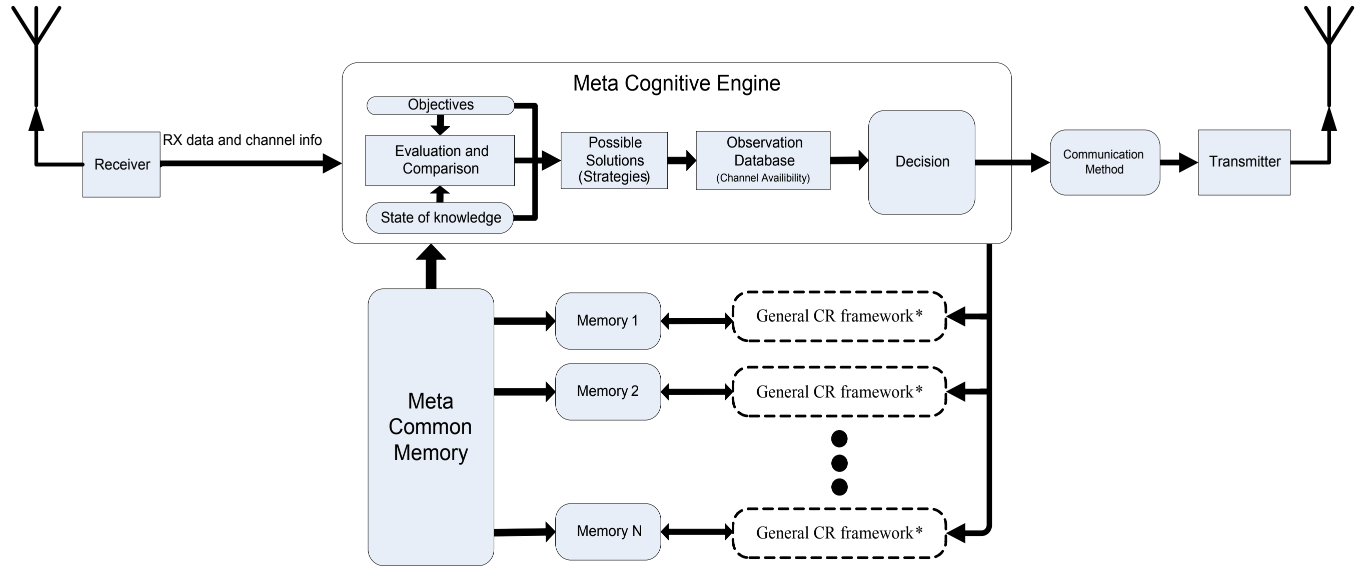

Fig. 2. Meta-CR Building blocks (* See Figure 1)

longer to run is only used when enough time is available. Although this approach has some performance benefits, it does not offer a particular automated method for performance evaluation between different kinds of available CEs. Furthermore, the meta-CE needs a powerful brain since it should be able to decide in various environments with different channel scenarios, and it must have a general form due to working with every CE with distinct algorithms. In this paper, we propose a preliminary meta-CE framework, which can collaborate with different CEs and it enjoys a solid brain that has more capabilities for working in different environment and channel conditions. This meta-CE simultaneously observes the available CEs' performance and characterizes the performance of their learning techniques in the present operating environment of the radio.

In our previous work on CE design, co-author Volos's first developed an efficient CE for link adaptation [7]. Two unique features that make this CE design significant are: first, the CE can provide estimates of its expected performance. This ability is very important because it allows the CE to provide those estimates to the radio's operator. Second, the CE it learns the abilities of the radio independently [36] from the operation objectives. This feature allows the CE to meet new objectives as fast as possible, minimizing the need to enter into a training phase. Ultimately, this should allow the CE to reach a point, where it no longer needs to learn the radios abilities, and it only has to perform optimization to meet the current objectives. It should be noted that the ability of the CE to provide confidence intervals and stop learning once it reaches a certain level of confidence is consistent with the goals of this paper.

Another aspect of our work that is relevant to this paper can be found in [37] & [38]. Providing predictable performance always is of paramount importance. Therefore, we evaluated the most critical phase of the CEs operation: the training phase. This is the time that the CE is called to maximize an objective, but it doesnt have enough knowledge about the radios abilities, and it has to experiment by sending training packets. This training performance analysis [38] is considered the precursor of the work of this paper. In [38] the training/learning analysis is performed by an expert engineer; in this paper, we build the foundations for the CE itself to be able to evaluate its own learning techniques and choose among them accordingly.

III. Techniques

In this section, we present the techniques used in this paper for implementing a meta-CE. The techniques are: first, performance characterization, which generates a learning curve for each CE technique and finds its unique performance characteristics. Second, techniques for scenario characterization that will be used to determine the performance of each CE technique under various operating scenarios. Finally, we present the meta-CE block diagram which classifies the best CE technique based on the channel conditions using the techniques of the previous two steps.

A. Performance characterization

A key goal of a CR is to find the best configuration meets its operating objective. For example, if the operating objective is maximum throughput, the CR's will aim to find the best communication method for maximum throughput. The CE technique in each step will choose configuration parameters and receive a reward based on the achieved throughput. Although, this decision-making process in each step is important by itself, the obtained reward is the major parameter that should be taken into account for evaluating the CE algorithm.

In order to evaluate the performance of the obtained CE technique, we utilize statistical performance metrics. In each step, the CE chooses a communication method for transmitting the data packets. We call each of these decisions and its reward, a time step hereafter. In order to get a smooth estimate, we repeat the process for several trials . The number of trials is highly related to all possible configuration methods. In this work, the sample size is calculated using (1) [39].

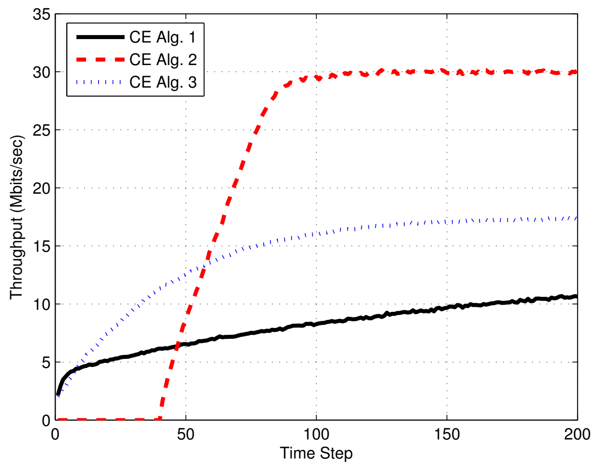

Fig. 3. Average Performance vs. Time Step

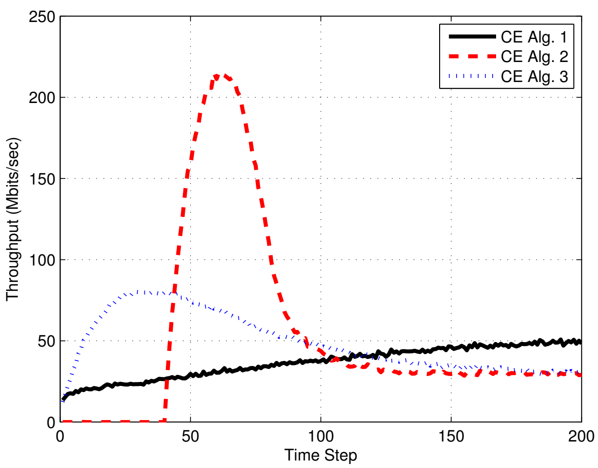

Fig. 4. Variance of Performance's Distribution vs. Time Step

$$n = \frac{N}{1 + N(e)^2} \tag{1}$$

where n is the sample size, N is the number of all possible configuration methods and e is the level of precision ($e \in [0, 1]$).

At each time step, we have a rewards distribution. The population size of these distributions is equal to the number of trials that were considered before. By graphing the distribution parameters in different time steps, we could show a specific aspect of the distributions. For example, if we graph the mean of distributions in each time step, this graph will present the progress in gaining rewards in the learning curve form, for a particular CE technique. Figure 3 shows learning curves (average performance) of three different CE techniques. As another example, graphing the variance (Figure 4) of the distributions in each time step enables to get insights on the variability of the CE's decisions.

In summary, learning curves can be very useful for comparing different agents and learning algorithms, for adjusting, switching and for combining two or more different algorithms. After obtaining the learning curves of CEs, we can make inferences regarding the regions of these curves. For example, there is a region in the beginning of some curves (e.g., see Figure 3 Alg. 2 from 0 to 40 time step) that we call it Zero Performance region. This region refers to a time or trials at the first stage of each learning curve that the agent tries operational conditions before obtaining its first successful response. Occasionally, this region occurs because of the prior knowledge bias that was used by the CE technique. Moreover, the slope of the curve shows the degree of conservatism or aggression of the technique's behavior. If the slope tends to be zero (parallel to the horizontal axis), it shows that the technique is more conservative and as the slope becomes steeper, the technique becomes more aggressive.

B. Performance evaluation

In the previous section, we explained how to generate the learning curves for each CE technique. At this point, we want to compare the learning curves and and find the best strategy. The performance evaluation depends on the objective function. For example, later in the paper we will introduce three different simple CE techniques and compare them. Two of these techniques are based on the ϵ-greedy algorithm. The ϵ-greedy strategy [40] is a simple strategy that uses the best communication method by 1-ϵ probability of the time (greedy). On the other hand, with probability ϵ, it uses a random communication method that is uniformly selected. This algorithm asymptotically finds the best communication method, however, the ϵ parameter controls how fast it will reach the best configuration (the higher ϵ, the faster it arrives at an optimal option). The first CE technique will work without having any initial information about the communication system but it has a high value of $\epsilon = 0.1$. On the other hand, we do have some prior information about communication system that should be used for the second CE technique. Although the second CE technique has a lower $\epsilon = 0.00001$, the prior information makes it more aggressive compared to the first and third CE technique. The third CE technique is based on the Gittins index strategy with a normal reward process and a discount factor equal to 0.9. Gittins proved that exploration vs. exploitation can be optimally balanced using a dynamic allocation index-based strategy [41]. This strategy maximizes the total sum of rewards collected over a long-term horizon. The strategy is simply to use the method with the highest Gittins index, which is based on the reward statistics of each method and must be estimated only when those statistics change (i.e., only when each method is used). We discuss the use of the Gittins indices in more detail in three of our prior publications [42], [7], and [38]. In Figures 2 & 3 we can see the mean and variance of these algorithms.

Before comparing these techniques, first we should determine the number of decisions that we can make during a specific channel scenario. The number of decisions are determined by the time that the channel metrics remain static, we call this time as "Application Time." By determining the application time, we are able to compare the CE techniques. For this purpose, we will use the sum of rewards up to specific application time (T):

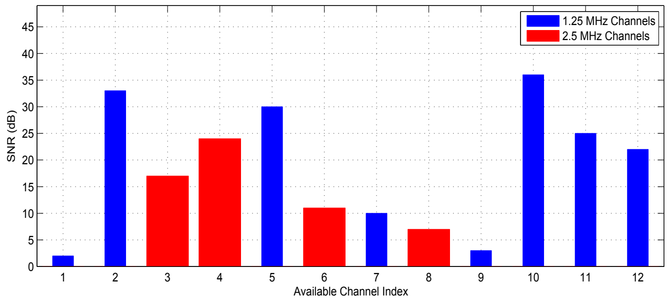

Fig. 5. Channel Scenario (SNR and bandwidth)

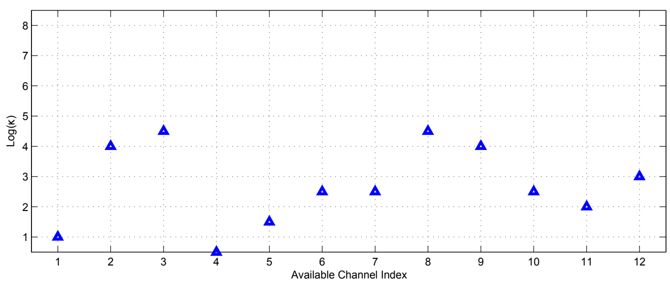

Fig. 6. Channel Scenario (eigen-spread)

$$R_T = \sum_{t=1}^{T} (R_t) \tag{2}$$

where R_t is the reward of a decision at a specific time step, T is the application time, and R_T is the sum of all rewards up to the desired time step.

For comparing CE techniques, the channel scenarios play an important role. For example, the more conservative CE (solid line in Figure 3) has better performance in the low SNR scenarios; however, the aggressive CE (dashed line in Figure 3) will outperform the others in the high SNR scenarios. Therefore, we should first determine the specific channel scenario that our CE techniques want to work on it. For instance, the learning curves on Figures 2 & 3 relate to the scenario that a CR has 12 channels available with different SNRs and bandwidth levels (either 1.25 or 2.5 MHz). We can see the metrics of this particular scenario in Figure 5 & 6.

C. Scenario characterization

Identifying the best configuration method is depended on the channel scenarios. Therefore, before the meta-CE can make any decisions the available channel metrics need to be determined. We represent the channel conditions by the average SNR γ_S and the eigen-spread κ (also known as the Demmel condition number) of the channel. In this work, we assume that the channel stays constant during the time required to decide and send a packet. It is well established that the SNR is an important performance predictor for any wireless system. We augment this with the eigen-spread of the channel since it can represent the quality of the available spatial channels (important for multi-antenna system performance). The eigenspread is defined as $\kappa = \dfrac{\lambda_{max}}{\lambda_{min}}$, where λ_{max} and λ_{min} are the maximum and minimum eigen-values of the HH^H matrix. A $\kappa \approx 1$ means that the spatial channels have minimum to no correlation and spatial multiplexing can be readily used. A high κ means that the spatial channels are highly correlated and spatial multiplexing is not feasible. A similar argument applies to diversity techniques. Other channel metrics can be used such as the mean excess delay, whether slow or fast fading is present, etc.

For distinguishing among different channel scenarios, the meta-CE uses a vector of SNR and eigen-spread. The size of this vector could grow too fast by increasing the number of channels that is available for our meta-CR. In this situation, meta-CE can use statistical pattern feature extraction to reduce the feature dimensions of each channel scenario so it can be effective for meta-CE classification methods. In this work, we use some statistical metrics such as, maximum, minimum, mean, variance and second largest value of all available channels' SNR also the mean and variance of the eigen-spread values. Our results show that, when we use these features alongside of reducing feature dimensions to seven, we could reach more than 92% accuracy in meta-CE classification method.

D. Meta cognitive engine

As it was shown in Figure 2, for implementation of the framework, a number of components are needed. In this framework, for each individual CE, a memory is considered in which the history of decisions made by each CE and the respective rewards are saved. In the meta-memory block, for each of the CE technique, by analyzing the data in each of their individual memory the respective learning curve is extracted.

On the overhead stage, there exists a meta-CE engine that receives this information and based on the objective function, performs comparison and evaluation between the individual CE algorithms. The result of this step is finding the more efficient solutions that satisfy the desired objective function. In some cases, it may combine two or more CE techniques to find the most proper solution.

In addition, there is another component that senses environment and obtains channel availability and metrics and sends these data to decision making part. Since decision making component wants to choose the best CE techniques based on channel scenarios, it needs some specific statistical metrics such as max and mean of all available channels SNR, therefore, observation component should prepare these data for decision making. The decision making component by considering the possible strategies and channel data will choose one or more CE techniques for transmitting data. Choosing more than one CE techniques needs additional investigation on the methods of combining the CE algorithms and is out of this paper context. In this research, we focus on detecting the best CE in various environments or channel scenarios.

The brain of our meta-CE is making decision component that it works with one classification method. In this work, we use nearest-neighbor classification method [43]. The nearest-neighbor classifier relies on a distance function among various patterns. there are different way for calculating the distance in this method that we use euclidean algorithm by

$$D(a, b) = (\sum_{k=1}^{d}(a_k - b_k)^2)^{1/2} \quad (3)$$

where $D(a, b)$ is the distance between a and b, d is the number of dimensions and a_k & b_k are amount of points in specific dimension.

For training our classifier, we need a dataset. Therefore, we define a dataset creator based on the distributions that we supposed for different channel metrics. For example, our dataset has 12 channels available and is created for SNR follows uniform (0, 50) and eigen spread approximately follows Weibull distribution for λ(scale parameter)=3 and β(shape parameter)=2 and we match it in our domain (0:0.5:12). The reason of creating dataset is considering various possible metrics for our classification. This component should be able to create well defined dataset, otherwise, if it doesnt cover possible values properly, it makes the meta-CE brain unable to make suitable decision for all distinct channel scenarios.

After creating our classifier, it predicts new arrival channel scenarios based on dataset points' locations. The classifier predicts classes so as to minimize the expected classification cost by (4):

$$\hat{y} = arg \min_{y=1,\ldots,K} \sum_{k=1}^{K} \hat{P}(k|x)C(y|k) \quad (4)$$

where $\hat{y}$ is the predicted classification, K is the number of classes, $\hat{P}(k|x)$ is the posterior probability of class k for observation x and $C(y|k)$ is the cost of classifying an observation as y when its true class is k.

The posterior probability for a new channel scenario vector $\mathbf{X}$ is calculated by

$$p(j|\mathbf{X}) = \frac{\sum_{i \in F(\mathbf{D},\mathbf{X})} W(i) 1_{Y(X(i)=j)}}{\sum_{i \in F(\mathbf{D},\mathbf{X})} W(i)} \quad (5)$$

where $p(j|\mathbf{X})$ is the posterior probability and $1_{Y(\mathbf{X}(i)=j)}$ means 1 when classifier = j, and 0 otherwise. Furthermore, $F(\mathbf{D}, \mathbf{X})$ returns the K nearest neighbors to the point $\mathbf{X}$ from the classification dataset $\mathbf{D}$; $W(\cdot)$ is the set of weights of the points in $F(\mathbf{D}, \mathbf{X})$.

In Figure 7, we can see the classification of 180 different channel scenarios. We assume that the meta-CE has 12 channels available. To demonstratethe classification, we used two dimensions as the scenario features. These features are the average of SNR and the average of eigen-spread. The background colors depict classes based on these features; however, the nodes' shape and color show the actual class. The accuracy of the classifier with just two features is not satisfactory; therefor, for increasing the classifier's accuracy from 85 % we add five more dimensions to bring the accuracy to 92 %.

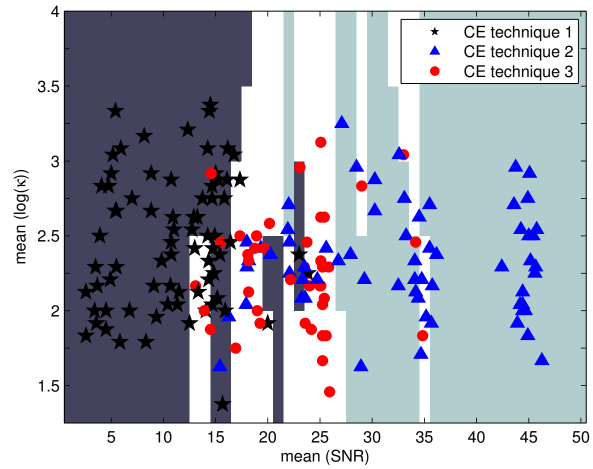

Fig. 7. Classification based on 2 dimensions

IV. Results

A. Discussion and results

In this research, for evaluating our meta-CE, we tested three CE techniques that were introduced in performance evaluation section. These techniques are distinct regarding their behavior (from more conservative to more aggressive). The main challenge of each CE technique is finding the appropriate communication method that can be used among all possible choices. Each communication method is defined by a combination of modulation type, coding and antenna techniques. In this research, we consider QPSK, 8PSK, 16, 32, 64, 128 and 256 QAM as a modulation type with eight error correction rates: 1, $\frac{7}{8}$, $\frac{3}{4}$, $\frac{2}{3}$, $\frac{1}{2}$, $\frac{1}{4}$, $\frac{1}{6}$ and $\frac{1}{8}$ and antenna techniques: VBLAST, STBC and MRC. For our channel scenarios, we consider an SNR in the range of 0-50 and the log of the Eigen spread in the range of 0-12 by step size of 0.5. Regarding these parameter settings, in each time step, the total options are 1320. Therefore, based on Equation 1, for 98% confidence interval, the calculated the sample size will be 864 that we rounded up to 900.

The component of dataset creator in meta-CE generates 180 random channel conditions that they cover various values of channel metrics (SNR and Eigen spread). In each channel condition, there are 12 channels that have different SNR, eigen spread and bandwidth.

After constructing all learning curves for all channel conditions, we analyze and compare the performance of the three different CE techniques. For each channel scenario, regarding which CE has larger summation reward in the specific application time, they will be classified. For using nearest-neighbor as a classifier, we should distinguish the channel conditions by considering some specific features such as maximum, mean and variance of SNR and Eigen spread between 12 channels. Our classifier is trained by using seven features and the calculated reward amount for each CE technique.

Henceforth, the meta-CE will choose the best CE algorithm for each channel scenario. Based on our classification, the accuracy of presented classifier in proposed scenarios is more

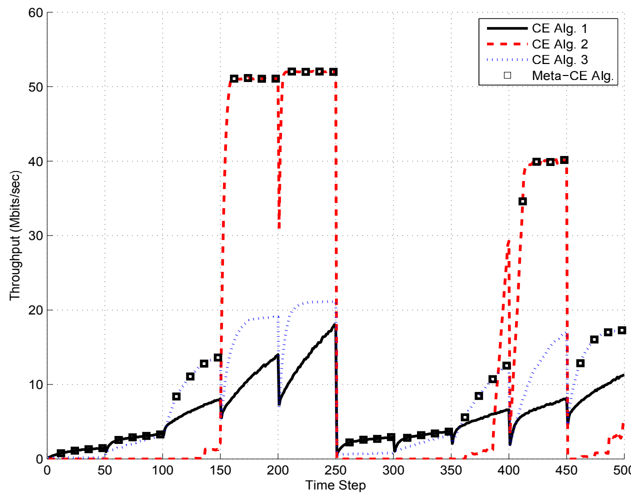

Fig. 8. Three different CE technique's means, CR has 12 channels available in each of 10 distinct scenario (meta choices specified in plot)

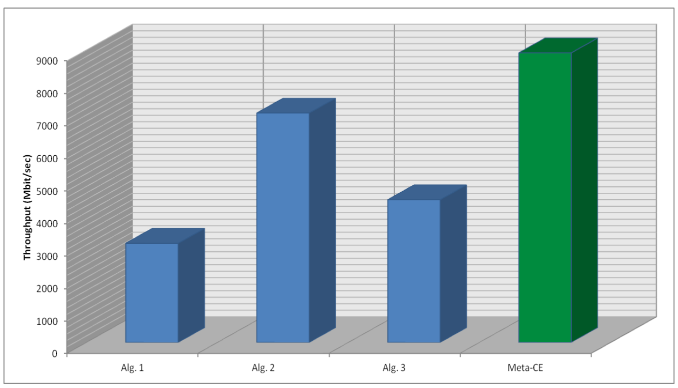

Fig. 9. Comparison between meta-CE and three different CE techniques (Summation of all rewards during 500 time steps for 10 distinct channels)

than 92%, which means, we could find the appropriate CE technique for each application time with a probability of 92 %.

We consider 10 different channel scenarios. These scenarios happen back to back, and we assume that each scenario is constant for 50 decisions (time steps). Figure 8 shows the respective constructed learning curve based on the mean of the trials in each time step for different CE technique.

In this test, when meta-CE works instead of individual CE techniques, it uses classifier in each ongoing channel scenario and based on the result of that, it selects the best one in distinct conditions. For comparing the performance of meta-CE with different CE techniques, we can see the summation of all gained rewards in each time step in Figure 9. And also, Figure 10 shows the average of rewards that each method is able to reach in different time steps. Based on the plots, it's clear that our proposed meta-CE shows more than 26% improvement compared with the best individual CE technique in this scenario.

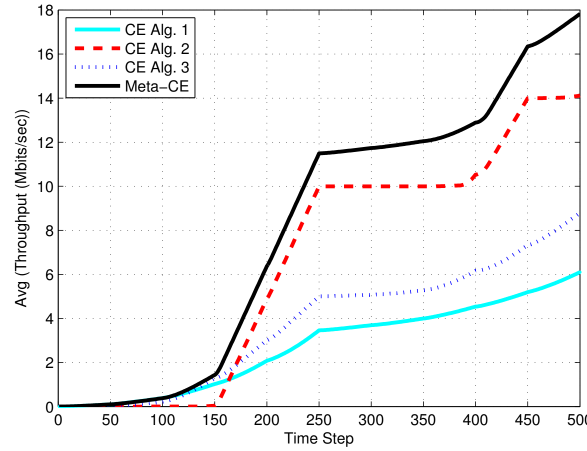

Fig. 10. Comparison between meta-CE and three different CE techniques (Normalized version)

B. Future Work

Meta-CR is a new research area, and more work needs to be done. The proposed meta-CE can find the best algorithm in each decision step; however, for making it more efficient we are working on models that enable meta-CE to combine two or more CE algorithms. By using them in the one decision step, we can enjoy benefits of different CEs simultaneously. Also, the CE may be able to produce new algorithms based on the available CE algorithms, which can be more effective for the operating conditions. Moreover, by using coherence time and bandwidth, the meta-CE will be able to predict how long the channel conditions may remain static with a high degree of confidence.

V. Conclusions

In this paper, we proposed the building blocks of a meta cognitive engine. First, we provided an overview of the metacognition concept and its utility. We showed that using metacognition can enhance the abilities of a CE system. Second, we characterized each CE learning technique by using statistical inferences and generating their respective learning curves. Third, we compared the learning curves of the CE techniques and we selected the best learning technique for different operating scenarios.

Fourth, we introduced our meta-CE brain and classified three different learning techniques in various channel scenarios. In fact, by using our classification method, the decision-making process of the meta-CE is accelerated. We showed that the accuracy of our classification technique has an acceptable rate (92.5%) in different conditions.

Finally, our results showed that a meta-CE could make more optimal decisions than each individual CE technique for the various channel conditions.

In this paper, the meta-CE selected among predefined CE techniques; in our future work, we are going to develop methods that allow the meta-CE to modify existing techniques and perhaps generate new ones that are going to be more suitable for the operating scenario.

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