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

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Outline

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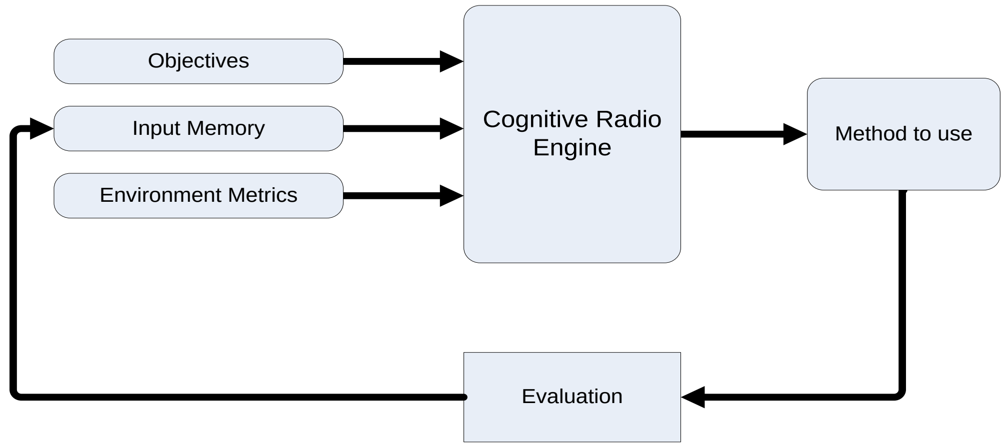
Introduction

- **Cognitive Radio** is a radio that uses intelligent agents for accomplishing its operational goals.
- **Intelligent agent** senses its environment, acts by using a method based on its experience, and observes its own performance to learn its capabilities, adding to its experience base.
- **Cognitive Engine** is an intelligent agent that enables a cognitive radio to have the desired learning and adaptation abilities.



2. Background

Background

- **User, policy domain and Radio domain**
  - based on GA, CBR and Multi-objective optimization (Rieser 2004 and Rondeau 2007)

- **Policy and Radio domain**
  - based on CBR (He et al. 2009)

- **Radio domain**
  - GA and swarm optimization (Newman 2007 and Zhao 2009)
  - Ant colony optimization (Zhao 2011)
  - CE with dynamic resource allocation (Zhang and Weng 2012)
  - Artificial neural network (Baldo and Zorzi 2008)
  - Predicate logic (Clancy 2007)

Meta Cognition

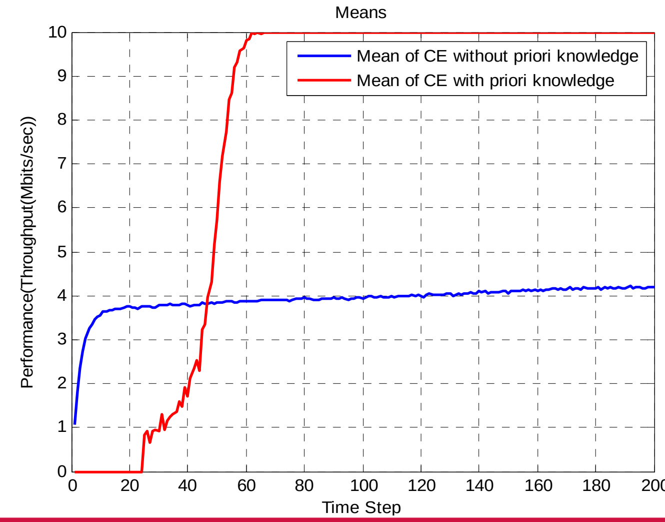
- **Meta-Cognitive Engine:** Meta-cognition is defined as "cognition about cognition", or "knowing about knowing". It can take many forms, it includes knowledge about when and how to use particular strategies for learning or for problem solving.

- **What can Meta cognition do for us in CR?**
  - Knowledge about CE techniques characteristics
  - CE techniques evaluation
  - Improve process by monitoring them
  - Using various CEs with different abilities at appropriate times, in different environments and in different regimes.

3. Techniques

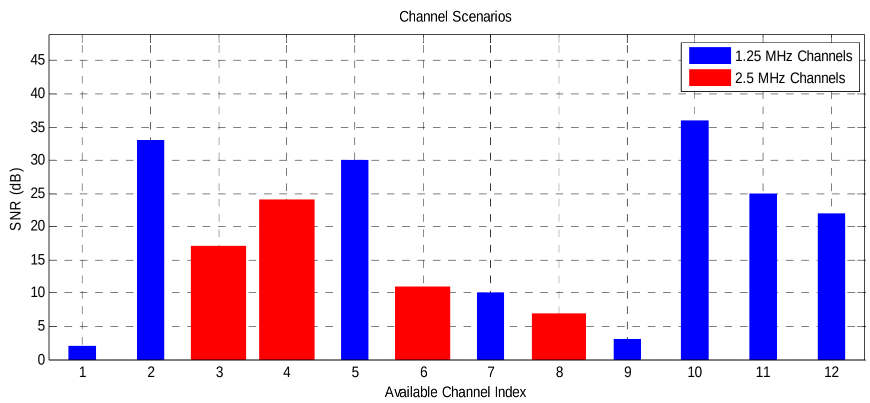
Performance Characterization

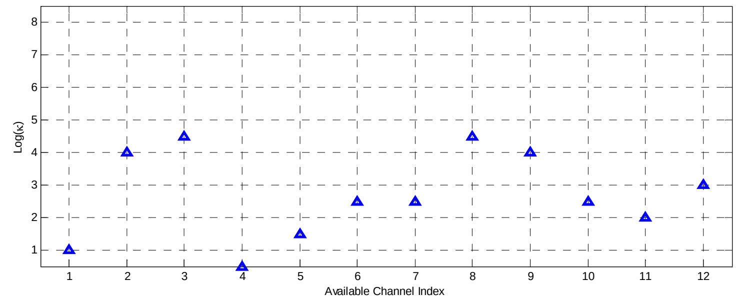
- The CR's aim is finding the best communication method that provides the admissible outcome based on objective.
- **Time step:** CE chooses a communication method for transmitting packets in each step. WE call each of these decisions and its reward, a time step.
- **Learning curve:** A learning curve 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".



Scenario Characterization

- **Signal to Noise ratio (SNR γ)**
- **Eigen-spread(κ)** (also known as the Demmel condition number) $\kappa = \frac{\lambda_{max}}{\lambda_{min}}$
- **Parameter Discretization**
  - The range for *log_{10}(eigen-spread)* is from 0 to 12, with equally spaced values.
  - The range for *SNR* is from 0 to 50*dB*, with 51 equally spaced values.
- For distinguishing among different channel scenarios, the meta-CE uses a vector of SNR and eigen-spread. And also we can use statistical pattern feature extraction to reduce the feature dimensions of each channel scenario.





Performance Evaluation

- For comparing different CE 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 will use the sum of rewards up to this specific time (T):

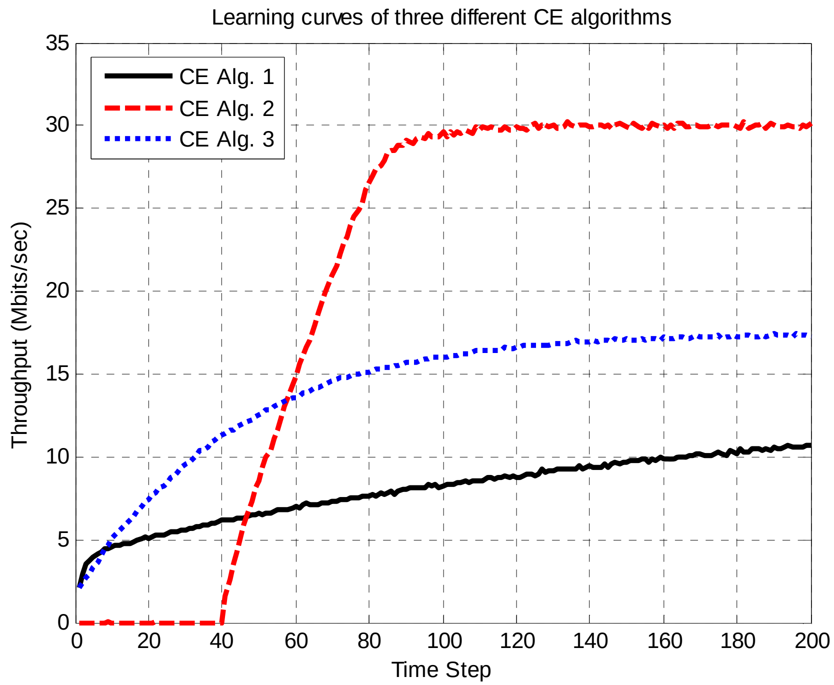
$$R_T = \sum_{t=1}^{T} (R_t)$$

Where R_t is the reward of one decision at one specific time step and R_T is the summation of all rewards up to desired time step T.

Performance Evaluation

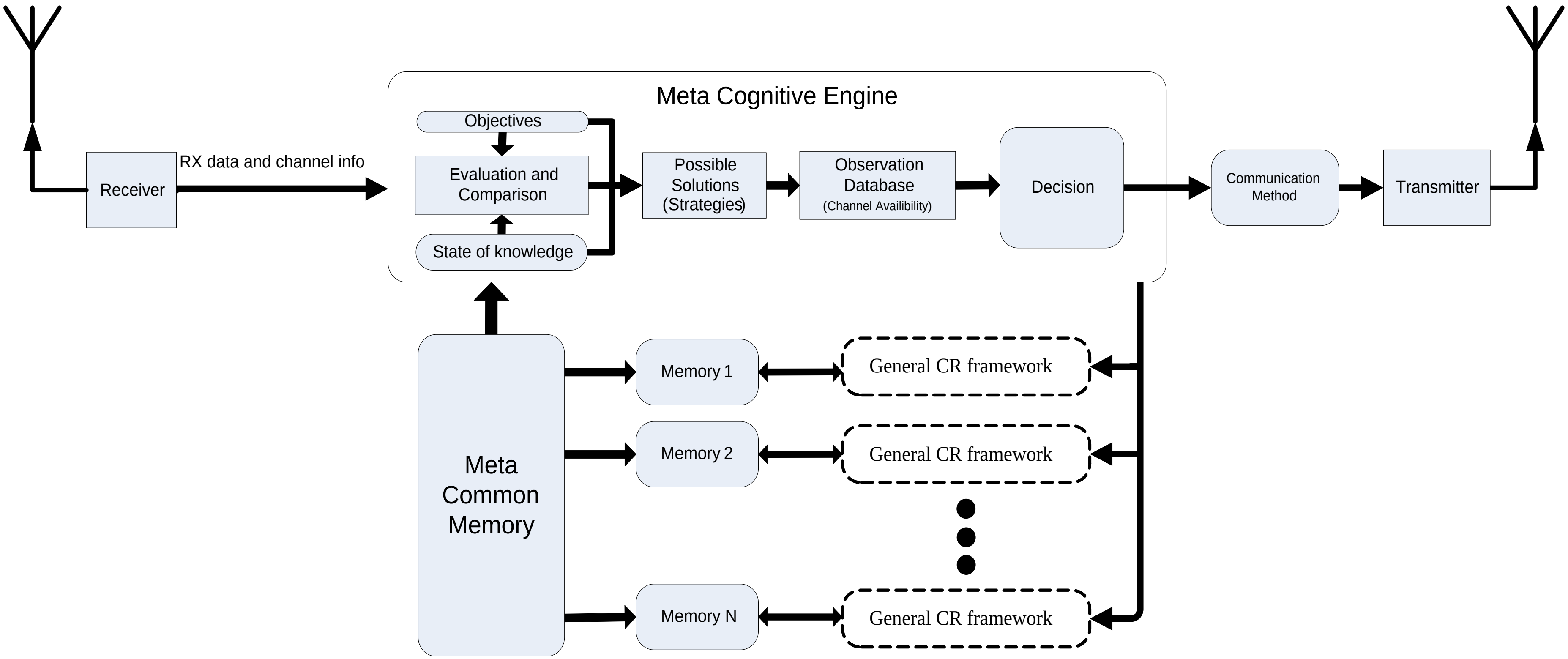
- Three different Cognitive Engine:
  - First CE technique is based on Ɛ-Greedy : Ɛ = 0.01 without any initial information
  - Second CE technique is also based on Ɛ –Greedy : Ɛ = 0.00001 with some priori knowledge
  - Third CE technique is based on the Gittins index strategy with a normal reward process and a 0.9 discount factor with some priori knowledge

(each time step represents 30 packets and each point on the graph was averaged 3000 times)



4. Meta-Cognitive Engine

Meta-Cognitive Engine



Meta-Cognitive Engine (cont.)

- The brain of our Meta-CE is the decision component that it works with one classification method.
- The nearest neighbor classifier relies on the distance function between various patterns.
- For training our classifier, meta-CE used a dataset with 180 different channel scenarios that each scenario has 12 channels available.
- The classifier predicts new arrival channel scenario so as to minimize the expected classification cost:

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

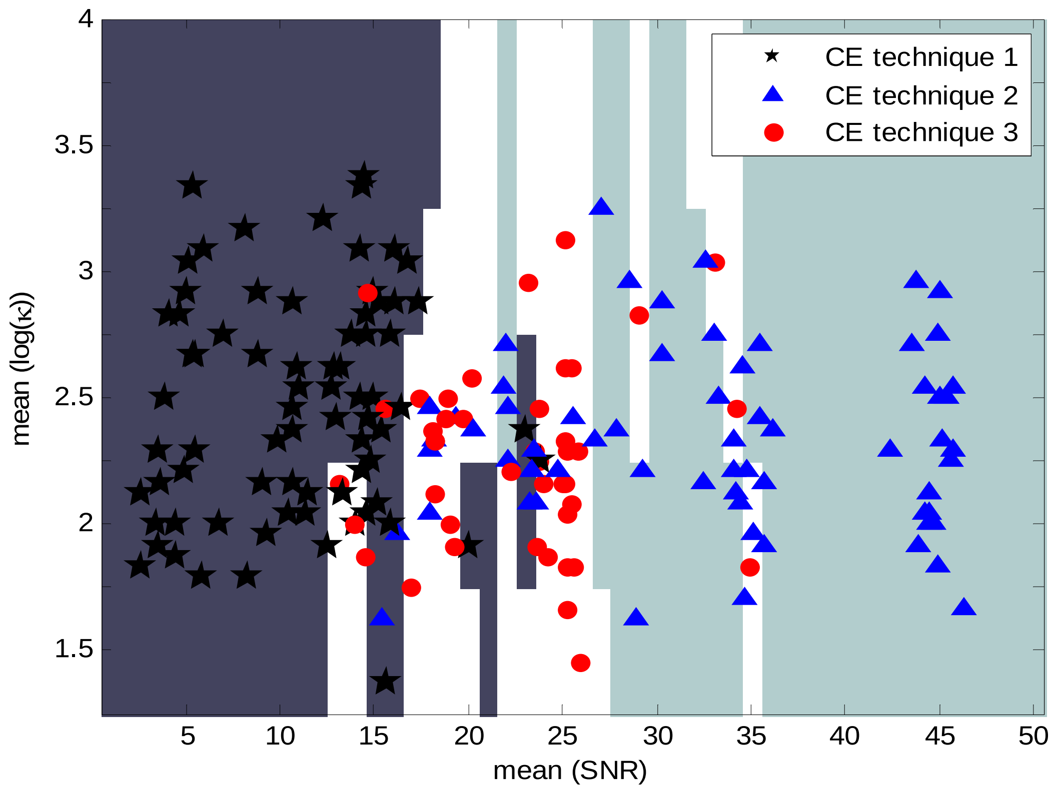
Where $\hat{y}$ is the predicted classification, K is the number of classes, $\hat{P}(k|x)$ is the posterior probability of class k for observation x and $C(y|k)$ is the cost of classifying an observation as y when its true class is k.

Meta-Cognitive Engine (cont.)

- The posterior probability for a new channel scenario vector X is calculated by:

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

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

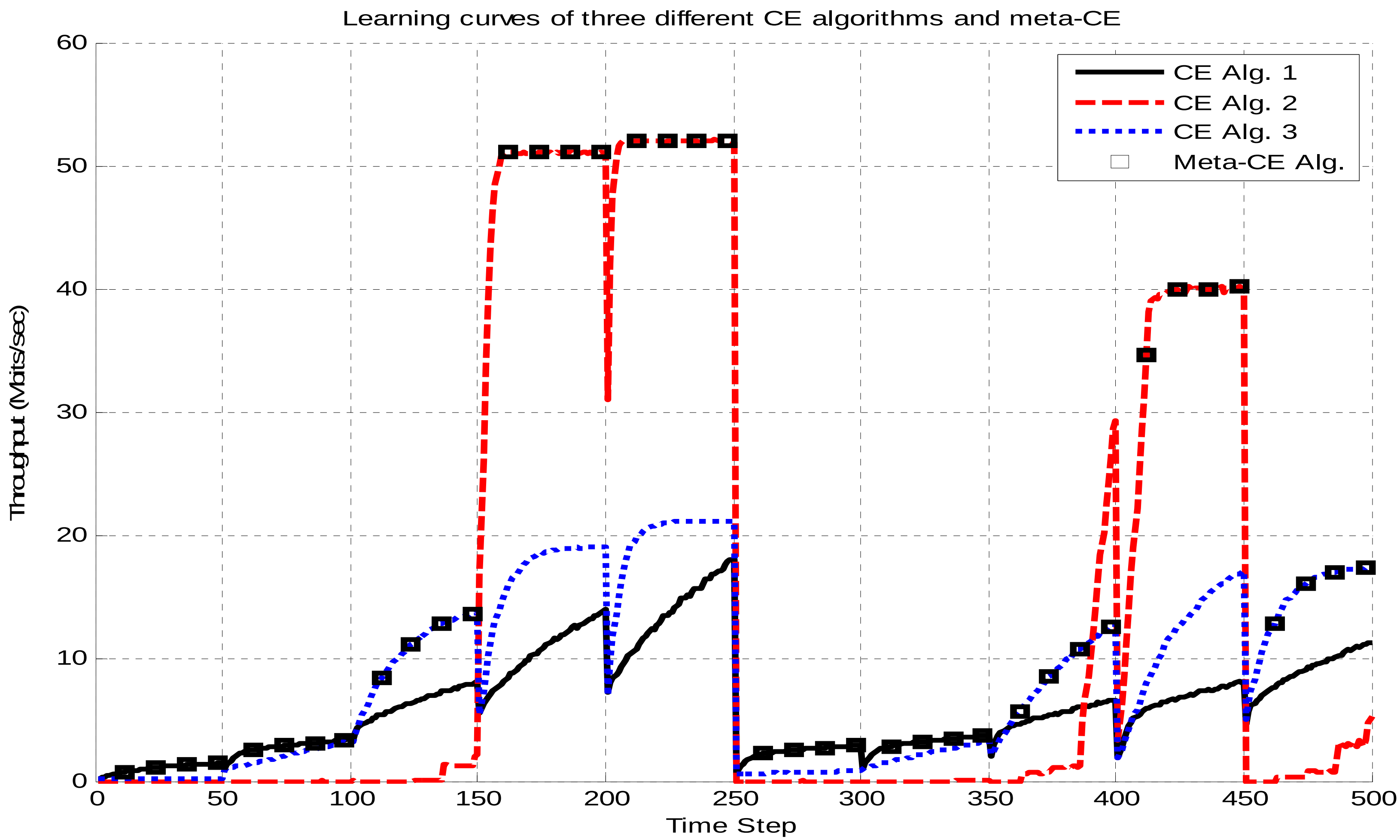


5. Results

Results

- For evaluating our meta-CE, we tested three CE techniques that were introduced.
- 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:
  - Modulations: QPSK, 8PSK, 16, 32, 64, 128, and 256 QAM
  - Error correction rates: 1, $^7/_8$, $^3/_4$, $^2/_3$, $^1/_2$, $^1/_4$, $^1/_6$, and $^1/_8$
  - Antenna techniques: VBLAST, STBC, and MRC
  - 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

Results (cont.)



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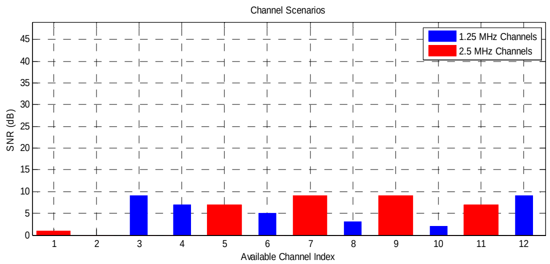

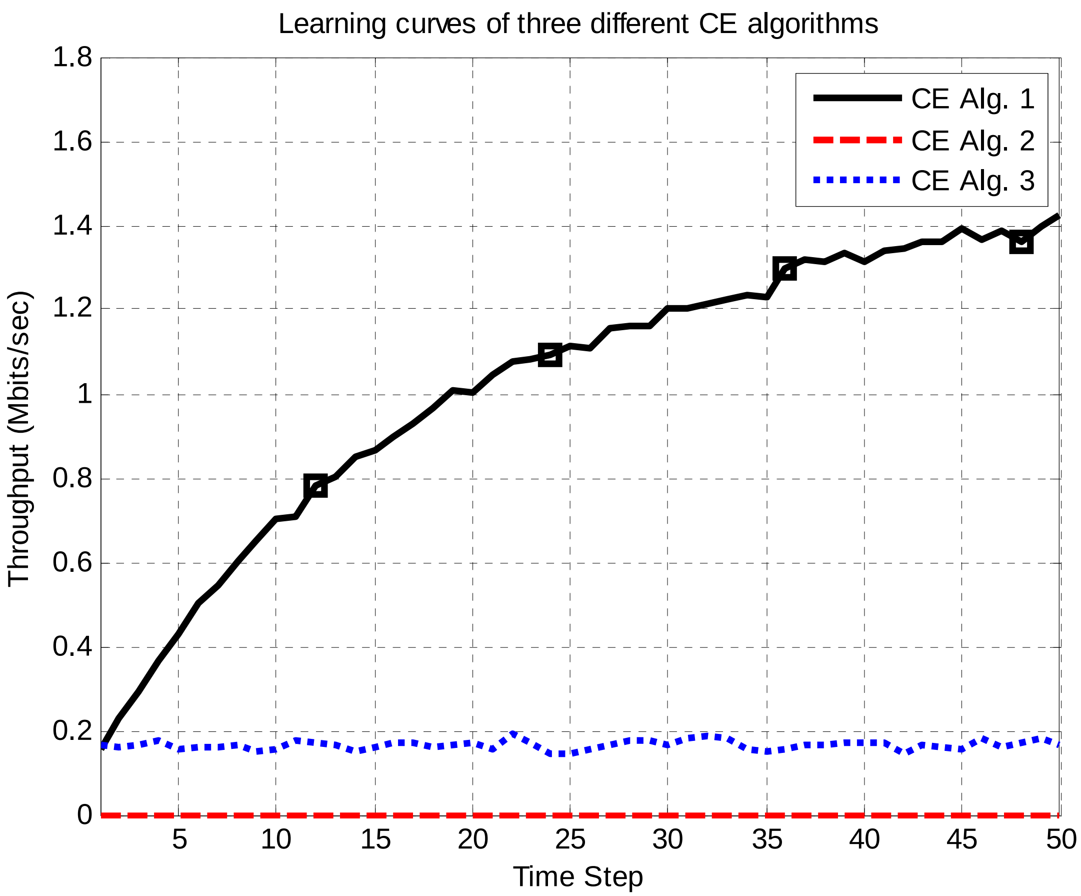

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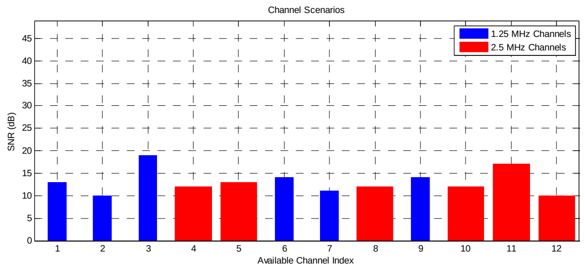

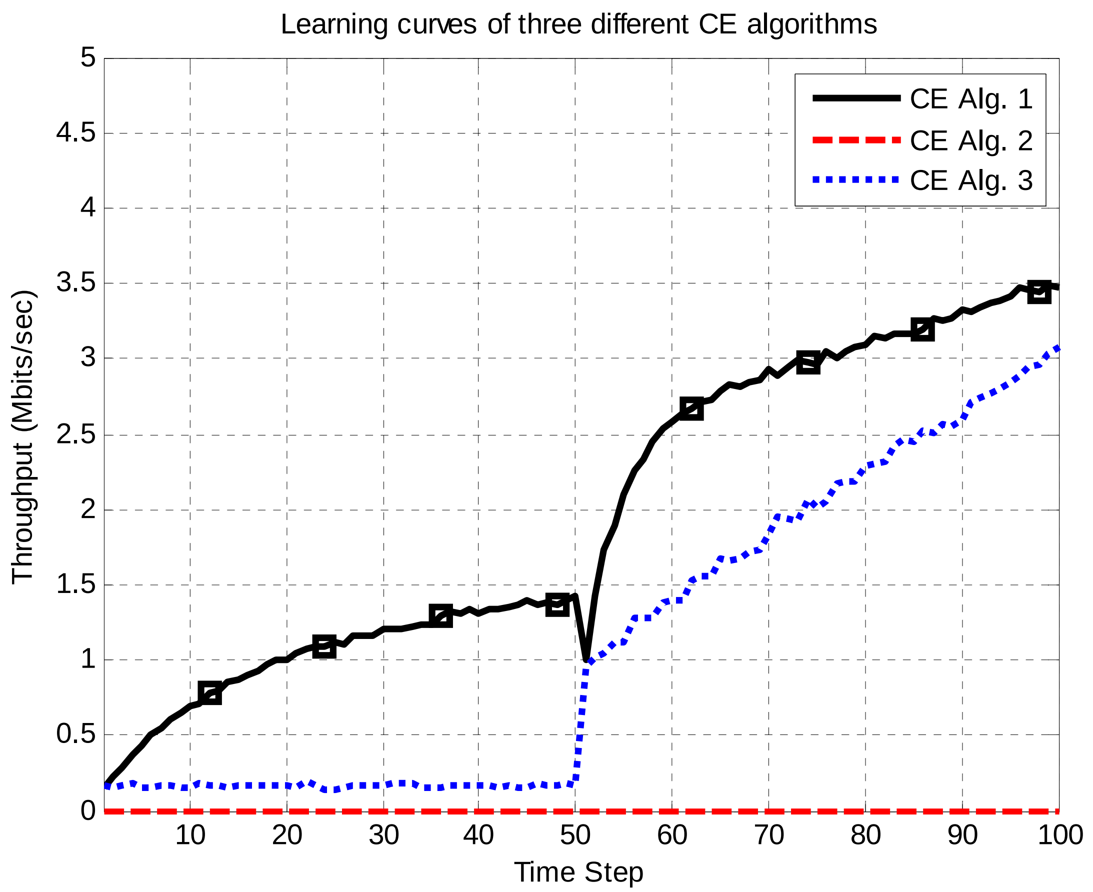

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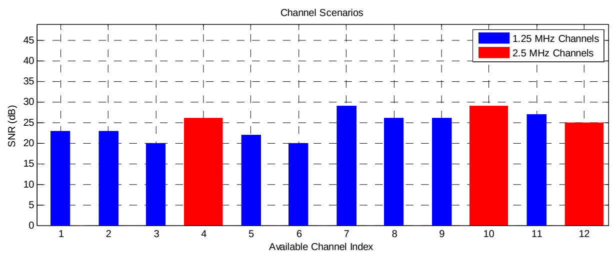

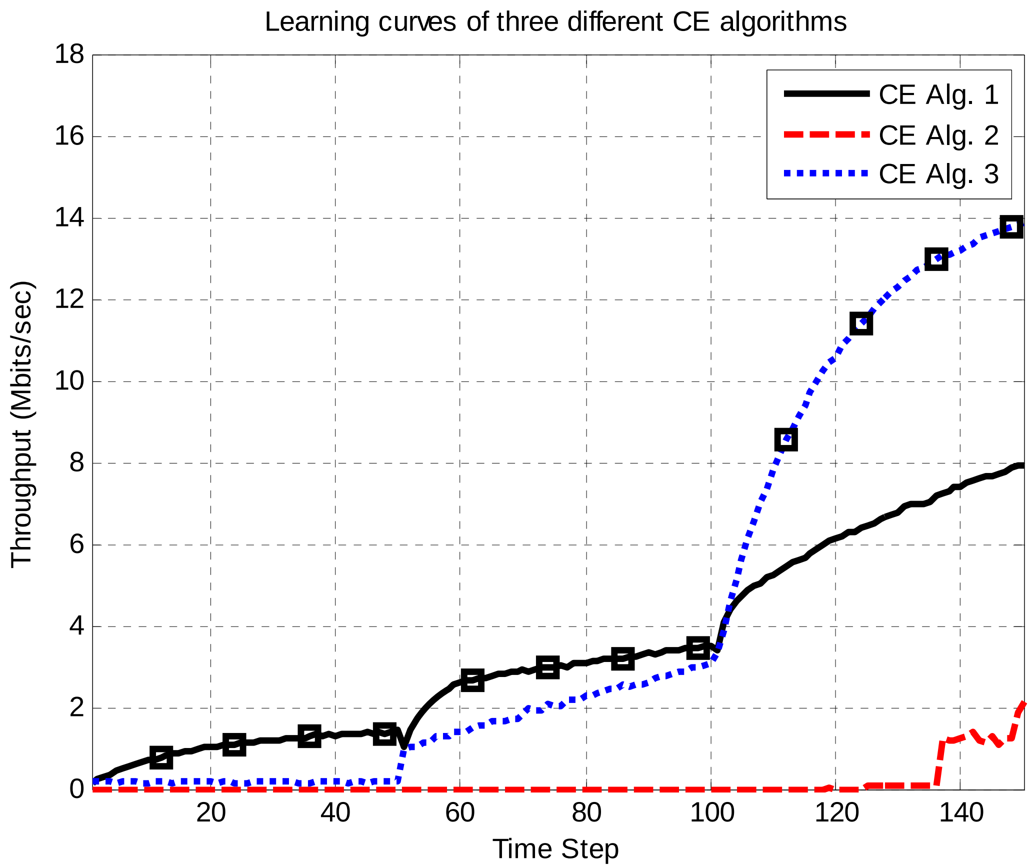

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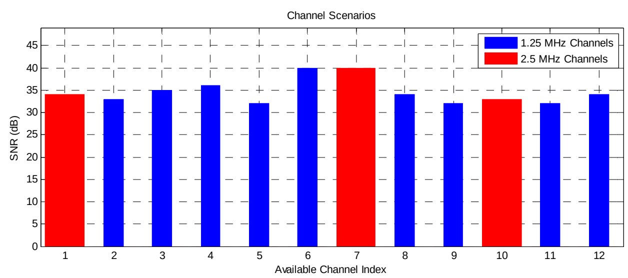

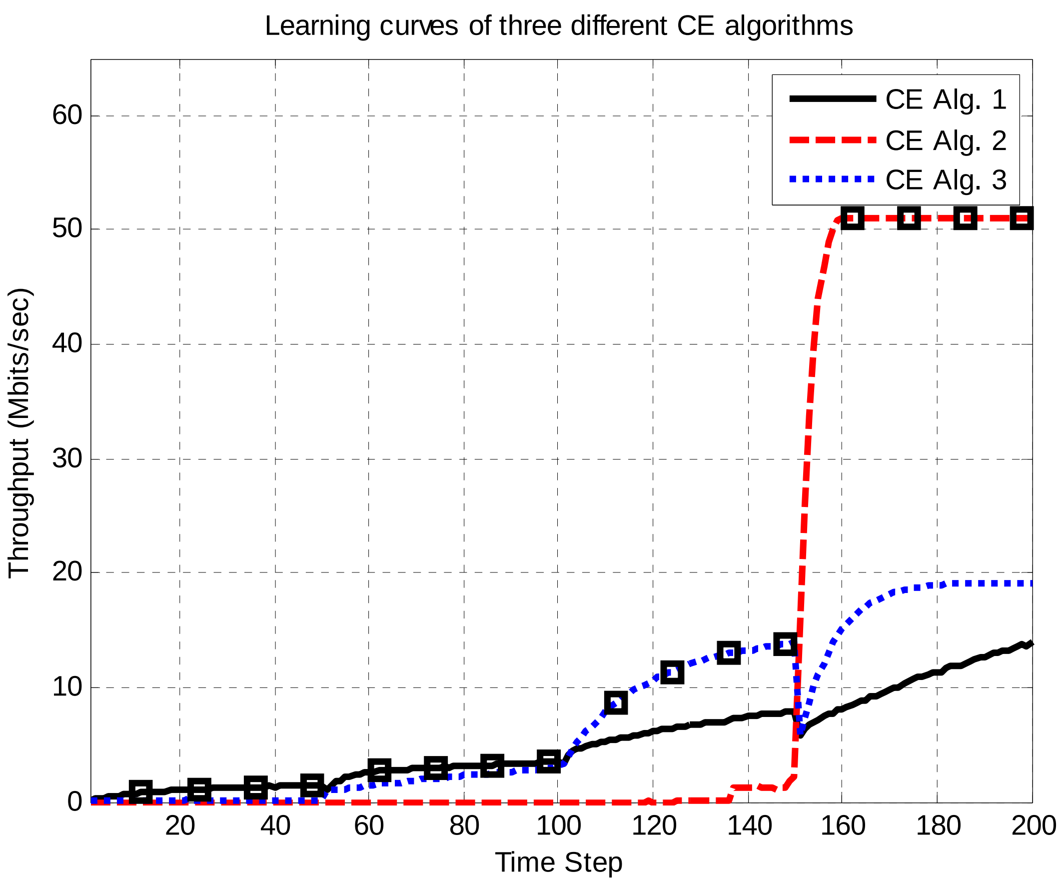

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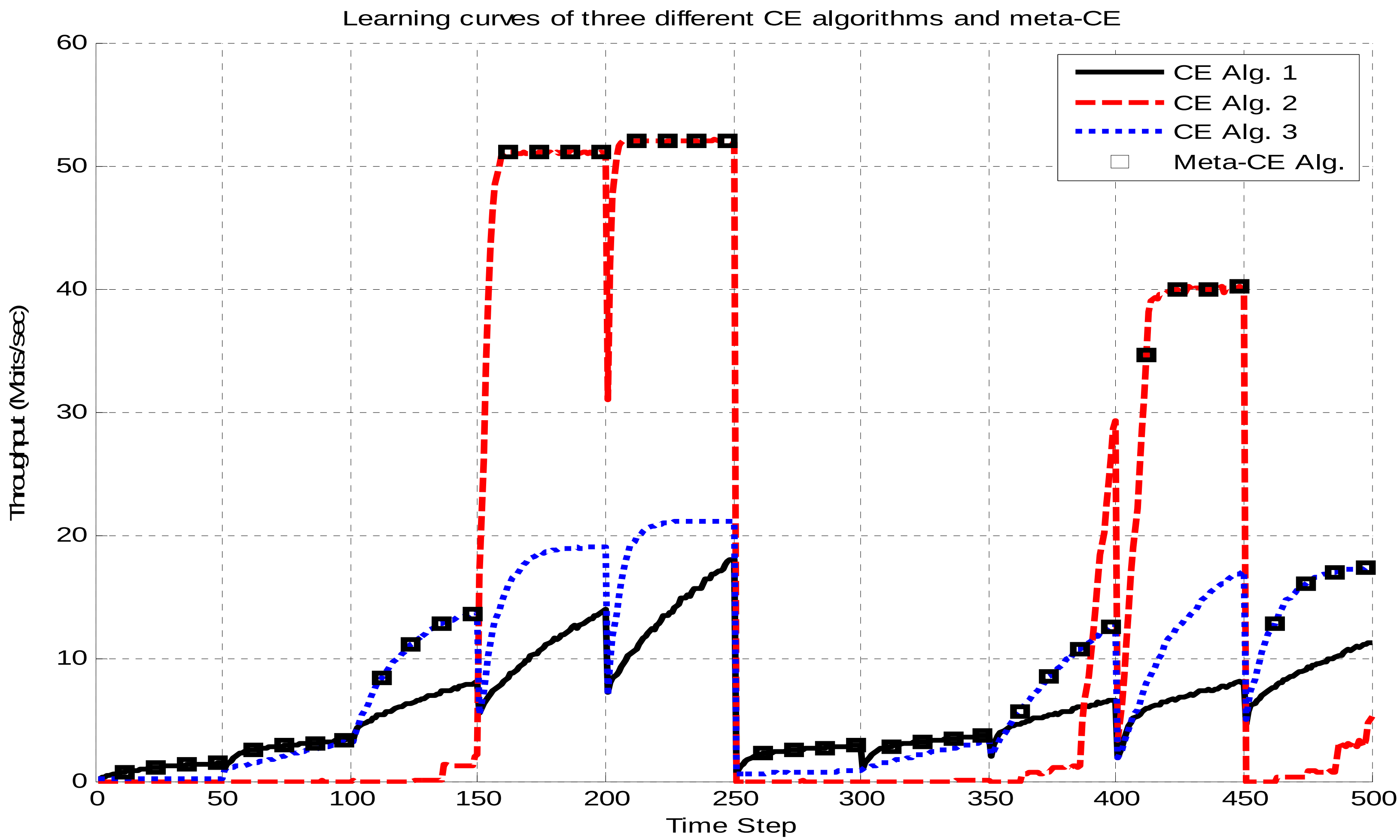

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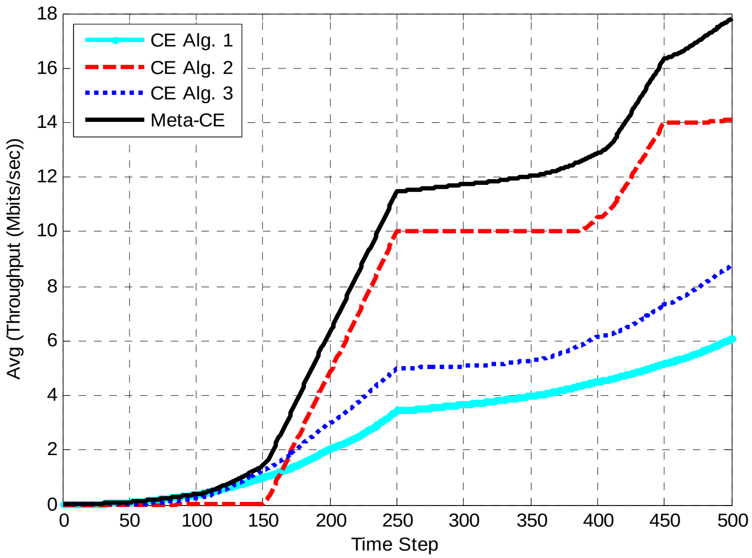
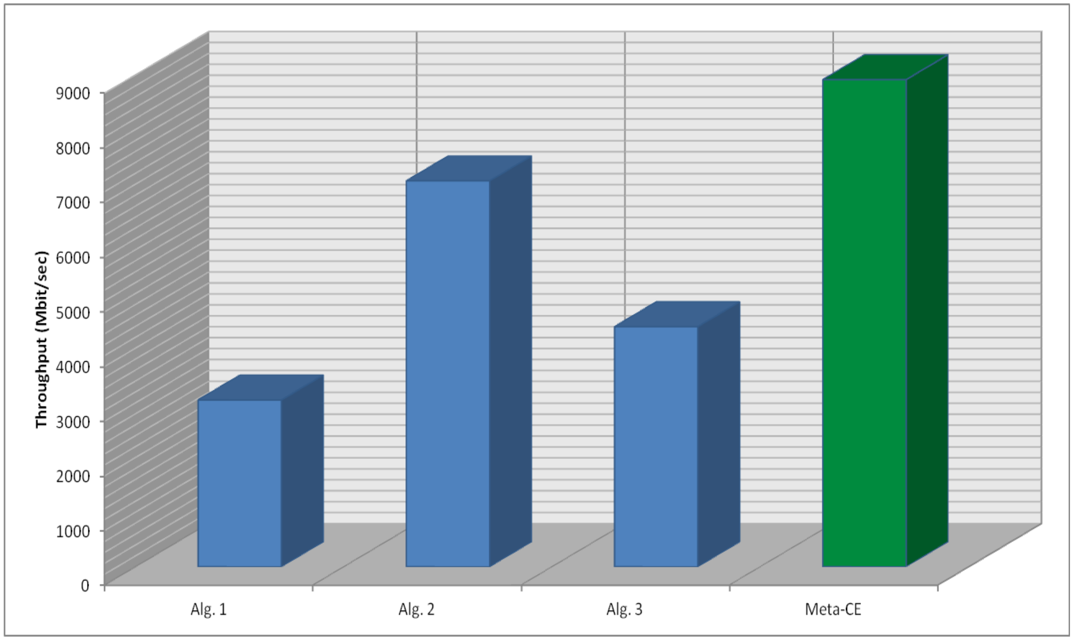


- Comparison between Meta-CE and individual CEs
- Average throughput in each time step



- More than 25% improvement in total throughput

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Summary and Conclusions

- First, we provided an overview of the meta cognition concept and its utility. We showed that using meta cognition 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.
- Finally, our results showed that a meta-CE could make more suitable and effective decisions than each individual CE technique for the various channel conditions.

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Thank You

Q&A