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A PREDICTIVE MODEL FOR COGNITIVE RADIO

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ABSTRACT

Advances in process technology, manufacturing, and architecture have ushered in an age of faster, smaller, and cheaper electronic devices. Emerging processor technology has made it possible to migrate applications that were traditionally implemented in custom silicon to general purpose processors (GPP). In the area of wireless communication, this transition has given birth to the field of software-defined and cognitive radio. These smart radios, or Cognitive/Sofware-defined Radios (C/SDR), can potentially make more efficient use of the available RF spectrum and adapt to a wide range of protocols and environments. One of the key benefits of having a C/SDR is it's ability to change communication parameters in response to changes in application needs and the radio frequency (RF) landscape. While understanding the effects of changing communication parameters is a critical precursor to the development of a predictive model, it is not the focus of this paper. This research builds upon our investigation of the affects of varying these communication parameters through the development of a predictive model. This model allows a C/SDR to dynamically modify its configuration in order to improve system performance.

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INTRODUCTION

A Cognitive Radio (CR) is a radio that has much of its functionality implemented in software, and is able to reason about its configuration based upon requirements and its environment. For example, one can envision an advanced CR network that dynamically allocates and reallocates spectrum or dynamically reconfigures itself in response to changes in policy and environmental conditions. The recent focus on homeland security, in light of the ineffective and inefficient use of the emergency bands, has given impetus to many of the scenarios that illustrate the promise of CR. One could imagine a government agency implementing a change to local spectrum policy in response to a disaster. These policy updates, when acted upon by a CR network, could affect allocation of spectrum to support increased demand during the emergency. This level of flexibility in a radio platform not only allows us to tackle the problem of spectrum utilization, but also serves as a terrific platform from which one can maximize the performance of the system by intelligently manipulating communication parameters. CR systems are ideally suited for research and experimentation with spatially aware applications, adaptive routing, cognitive media access control (MAC) layers, and mutable physical layers.

In our pursuit of developing a viable CR platform, we contend that it is crucial to understand how varying parameters at the physical, data link and network layers can affect the performance and reliability of a wireless system. Understanding how these parameters affect performance allows the researcher to consider how a system might be optimized [1]. We see this as a first step in the development of an algorithm for cognitive radios. Once the performance implications of varying these parameters is understood and a model has been developed, one must consider secondary issues. These issues include decisions about when and how to change configurations, how these changes are propagated throughout CR network, and how much time can be spent computing a change in configuration. While these are all important research questions, this article focuses solely on the development and presentation of the predictive model. Additionally, we will not discuss in detail the process used to identify the significant factors and their interactions (see Weingart et al. for further explanation) [1].

Design of Experiments (DOE) is a methodology that has been largely used in the process industries to optimize production lines [2]. Recently it has been applied with some success to mobile adhoc networks (MANET) [3], [4], [5]. DOE requires the identification of factors (inputs to an experiment with differing values or levels) and responses (outputs of the experiment, observations, measures). A series of experiments is run with permutations of the levels of the factors and the responses recorded. DOE, through statistical methods, is able to identify the significant factors or combinations of factors that impact the response of interest and produce a model for prediction of the response. Additionally, there are instances where the predictive model created by DOE does not provide an adequate predictor due to irregularities or partitioning of the data set. In these cases another method should be applied. We will show later how DOE does not provide an adequate predictor for latency, whereas a regression tree is able deliver the desired utility. The ultimate goal of this research is to utilize the outcome of the DOE analysis to formulate a methodology for dynamically selecting a CR configuration. This configuration will meet a primary objective (i.e., maximizing throughput) while meeting secondary (i.e., minimize latency) or tertiary (i.e., minimize power consumption) performance goals.

This paper is organized as follows. The following section describes related work in CR and application of DOE. Next we present the experimental design. This is followed by an introduction of the predictive model and how it could be used in a cognitive platform. We conclude with a summary of our findings and a presentation of future directions and research opportunities.

Related Work

Research in the area of cross-layer optimization for wireless systems has been an area of considerable focus in recent years. Others have also spent a considerable amount time and effort investigating cognitive radios. However, the potential of improving the performance of a wireless system by combining cross layer optimization with cognitive systems is just emerging as a research area.

Much of the work in the area of cross-layer optimization focuses on enhancing throughput, Quality of Service (QoS) and energy consumption [6], [7], [8]. These cross-layer optimizations tend to focus on two layers of the protocol stack with the goal of enhancing a specific performance measure. As such, they do not consider multi-factor variation nor do they consider affects of this variation on inelastic applications, such as Voice over Internet Protocol (VoIP). Kawadia and Kumar present an interesting critique of cross layer design in [9]. They warn that cross layer optimization presents both advantages and dangers. The dangers they discuss include the potential for (1) spaghetti design, (2) proliferation problems and (3) dependency issues. Such cautions (and others that we shall identify) are easily overlooked in the hopes of gaining sometimes marginal performance improvements. Therefore, understanding the significance of the potential improvements is an important step to consider.

Given that the interactions among a set of parameters is determined, the next step is determining the significance of these interactions. In other words, which interactions provide the best response in a given situation. Vadde et al. have applied response surface methodology and DOE techniques to determine the factors that impact the performance of mobile ad hoc networks (MANETs) [3], [5], [4]. Their research considers routing protocols, QoS architectures, media access control (MAC) protocols, mobility models and offered load as input factors and throughput and latency as response factors. Their analysis demonstrates the usefulness of these techniques and shows where certain input factors can outperform others within a MANET.

Haykin provides a thorough overview of cognitive radios and describes the basic capabilities that a "smart" wireless device might offer [10]. Others describe techniques for applying CRs to improving the coordinated use of spectrum [11], [12]. Sahai et al., describes some of the physical layer limits and limitations of cognitive radios, including the difficulties associated with determining whether or not a radio frequency band is occupied [13]. Nishra has implemented a test bed for evaluating the physical and data link layers of such networks [14]. Additionally, Thomas describes the basic concept of a CR network and provides a case study to illustrate how such a network might operate [15]. It is also worth noting that the standards communities are focusing on cognitive radios. The IEEE 802.22 group is developing a wireless standard for the use of cognitive radios to utilize spectrum in geographically separated and vacant TV bands [16]. Also in the IEEE, the P.1900 workgroup is examining the general issue of spectrum management in next generation radio networks.

Predictive Models For Cognitive Radios

The thesis of our work is that we should be able to *predict* which system configuration delivers a specified throughput or latency goal based on a set of possible system configuations, environmental conditions and an expressed demand. In practice, this is a continuous process, as illustrated in Figure 1. In our process, we develop a predictive model that is used to configure a software defined radio; that radio is then used for communication and information on the achieved throughput (or latency) is recorded. The collected performance data is used as input into the prediction mechanism thus allowing derivation of a new predictive model.

We expect this to be a continuous process since environmental impacts will change the interaction of different configuration factors. In practice, we need to determine a starting point for the system configuration and, more importantly, determine which existing methods are effective for predicting specific system properties such as latency or throughput. In this paper, we seek to demonstrate that *multi-linear models* are sufficient for predicting a system configuration that achieves a target bandwidth. We have also found

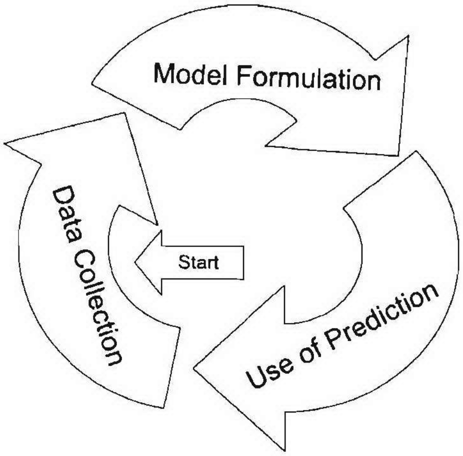

Fig. 1. Prediction Cycle

TABLE I
THE SET OF MUTABLE PARAMETERS

Parameter	Settings	Layer
Automatic Repeat Request	off/on	MAC
Framesize	2048,9216,18432 bits	MAC
Forward Error Correction	off/on	MAC
Jammer Noise Level	1,4,11 mW	Physical
Bit Rate	1,2 Mbs	Physical
Transmit Power	5,32,100 mW	Physical
Selective Queueing	off/on	Network

TABLE II
THE SET OF METRICS

Metric	Units
Bit Loss	Percent
Latency	Seconds
Jitter	Seconds
Throughput	bps

that these models are not sufficient for predicting latency and an propose alternate prediction mechanism based on decision trees. Our use of multi-linear regression models is most easily understood using the terminology of Design of Experiments and ANOVA techniques; this framework allows us to demonstrate which factors in our system have a significant contribution to predictive accuracy.

What follows is a description of the design and setup of our experimental simulation environment and a brief introduction to DOE. We also describe how we apply DOE techniques in identifying the statistically significant inputs and their effects on our performance metrics. These input parameter interactions and effects form the basis of our predictive model for cognitive radio.

Design of Experiments

Design Of Experiments (DOE) is an approach for determining cause and effect relationships within a system or process [2]. DOE is ideally suited to answer questions of the form, "What is the best configuration of input factors or combination thereof to maximize an output or response?" Use of the DOE methodology requires a set of structured tests wherein permutations are made to the input parameters and the effects or responses of those changes are analyzed. Thus, DOE provides a method for understanding the relationships among input parameters and response metrics. The DOE process allows researchers to determine the significance of input factors acting alone as well as in combination on the measured response. DOE makes no assumptions about how the various inputs interact or impact the outputs. This technique requires a set of experiments that produce adequate and statistically significant coverage of the experimental space. Mechanically, it relies on the Analysis Of Variance (ANOVA) statistical method to provide an assessment of the significance of the test results. The core statistical process at work is the calculation of the *F-test* [2]. This test compares the variance among the treatment means versus the variance of the individuals within the specific treatments. Another way of looking at F is as a ratio of signal to noise.

Procedurally, our first step in using DOE was identifying the input variables and the responses. Each input variable has a number of levels. The input variable is varied along each of the levels and the result is measured. For our purposes we measured bit loss, latency, jitter, and throughput. Table I lists inputs parameters and their settings. One could imagine that these parameters as well as others would be available to a cognitive process running on a "smart" radio platform. Each of the simulation trials examines the performance of the experimental system at each of the potential parametric settings. Table II is a list of the responses or metrics by which we evaluate each mutation of the settings. One can independently look at the performance of any of the parameters (alone or in combination with other parameters) against any one of the metrics used to evaluate the system. We made use of a software suite developed by Stat-Ease to assist in the DOE calculations [17]. This system also generates an equation for predicting a response given a set of input parameters. This equation can be used by a cognitive system to react to changes in environmental conditions or requirements. Later, we present an equation as part of a methodology for predicting cognitive radio's performance and configuration.

Simulation Tool and Experimental Setup

To simulate the effects of the input parameters on the responses, we used the OPNET Modeler simulation environment [18]. This software suite provides a rich and readily

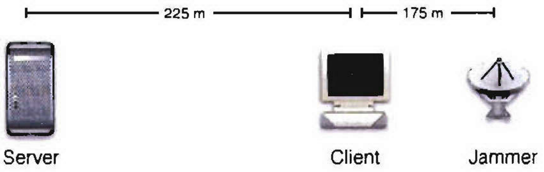

Fig. 2. Experimental Layout

extendable network simulation and modeling environment. While OPNET provides a wireless networking module for the media access control (MAC) layer, to obtain the flexibility that was required for interactions spanning protocol layers, we found it necessary to develop our own module. This module allows adaptation of the input parameters on a per packet basis. The simulation itself consisted of two nodes communicating in the presence of a noise source (e.g., a noncooperative node on a different network, an environmental noise source or a jammer). Figure 2 shows the physical layout of the two communicating nodes in relationship to the noise source. The uncooperative (or jamming) node is emitting noise in a Poisson distribution centered around an interarrival time of 0.0125 seconds and a burst length of 2048 bits at one of three power levels (see Table I). The physical layout of the nodes and noise source is fixed across all of the trials. In the development of our predictive model, we analyzed a broad range of noise parameters including different distributions, inter-arrival times and power levels. We settled on a group of settings that provided appreciable interference without overwhelming the communicating nodes.

RESULTS AND DISCUSSION

The following section reports the results of our simulation work. We begin by providing a brief summary of our prior work in applying DOE to determine the significant factors for reconfigurable radio devices. We then describe the technique a CR could use to dynamically reconfigure in response to a change in application goals or requirements. The section concludes with an evaluation of the predictive models for determining expected throughput and latency.

Background

In our earlier research [1], we were able to determine the set of factors and interactions that significantly impact the performance of the system. We conducted trials that were designed to cover a range of traffic sent between nodes in the presence of a noise source. FTP and VoIP traffic were selected due to their distinct tolerances for latency, jitter, throughput, and bit loss. The parameters that we examined included ARQ, frame size, bit rate, transmit power, FEC, and selective queueing (as described in Table I). Each of the trials was analyzed across the dimensions of the parameters and general trends were highlighted through exhaustive interaction of all parameters. We measured jitter, latency, bit loss and throughput as each factor was varied across all combinations of the other factors (i.e., a full factorial analysis). From this, we were able to determine the statistically significant single and multi-factor effects. In this paper, we use the results of this work to single out those factors and factor interactions that most impact a response, thereby providing the foundation from which to develop a predictive model.

TABLE III
ANOVA FOR AVERAGE THROUGHPUT

Source	Sum of Squares	df	Mean Square	F Value	P Value Prob<F
Model	1.28E+14	20	6.40E+12	2362.45	<0.0001
A-J-Power	1.10E+12	1	1.10E+12	405.19	<0.0001
C-ARQ	1.31E+09	1	1.31E+09	0.48	0.4872
D-FrameSize	1.43E+12	2	7.13E+11	263.33	<0.0001
E-DataRate	1.20E+14	1	1.20E+14	44194.37	<0.0001
F-Power	2.84E+12	1	2.84E+12	1046.79	<0.000
G-FEC	8.30E+09	1	8.30E+09	3.06	0.0804
AC	2.63E+10	1	2.63E+10	9.72	0.0019
AE	2.55E+10	1	2.55E+10	9.42	0.0022
AF	2.87E+11	1	2.87E+11	106.12	< 0.0001
AG	1.10E+10	1	1.10E+10	4.07	0.0438
CD	2.05E+11	2	1.03E+11	37.91	< 0.0001
CE	2.75E+11	1	2.75E+11	101.65	< 0.0001
CF	4.70E+10	1	4.70E+10	17.34	< 0.0001
CG	2.57E+10	1	2.57E+10	9.49	0.0021
EG	6.75E+11	1	6.75E+11	249.09	< 0.0001
FG	2.97E+11	1	2.97E+11	109.62	< 0.0001
A^2	5.54E+10	1	5.54E+10	20.44	< 0.0001
F^2	9.74E+11	1	9.74E+11	359.71	< 0.0001
R^2: 0.974					

Technique for Determining a Configuration

The predictive models presented in the next section are guided by a set of requirements. In general, a CR would operate as follows: (1) Use the regression model to determine the set of configurations that could meet the initial primary response requirement. For example, an application might seek to achieve an average throughput of 1.75 Mbs. Then, (2) Using the set of configurations resulting from step one, a CR would eliminate those configurations that do not match the secondary response requirement. In this step, the CR might use an additional predictive model to determine the set of configurations that meet its latency requirement. Thereby, further reducing the set of potential configurations. Finally, (3) If further reduction of the configuration set is desired, the CR could eliminate potential configurations via a third criteria o r requirement. Here, the CR could select the configuration that minimizes transmit power.

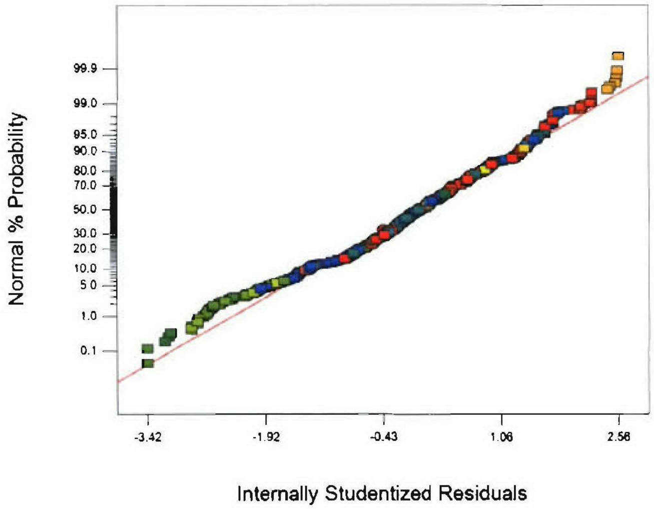

Fig. 3. Predicted Throughput Normal Plot (R^2: 0.97)

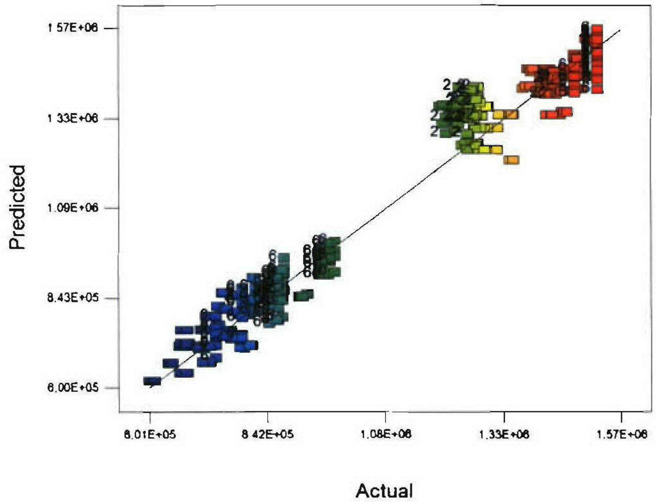

Fig. 4. Actual vs. Predicted Throughput (*numbers indicate stacked pts*)

Predictive Model for Throughput

This subsection presents the results of DOE analysis with respect to average throughput. Table III shows the ANOVA for the significant factors (non significant factors were eliminated from the model). First, it is worth noting that R^2, a measure of how well a regression line approximates the real data points, is 0.97. This model provides a nearly perfect fit, in other words, based on the data that we have collected the relative predictive power of our model is very good. The table also indicates the most significant parameters, as shown by high F values, with Data Rate and Power having the highest result. Figure 3 shows the normal plot for the model and indicates that the residuals follow a normal distribution. This demonstrates that the model satisfies the assumptions of the analysis of variance. Figure 4 shows the plot of the predicted vs the actual values. Notice the two groupings in the chart indicate the relative predictive power of the model based upon the two data rates used (1Mbs and 2Mbs). The fitted second-order response function for this model is given in Equation (1). Because some of the factors are not continuous (rather they are categoric), one cannot simply plug the actual values for the factors into the function. In order to get a predicted response one needs to plug the values for the levels of the response into the equation. A summary of the values for the two and three level factors is given in Table IV. The levels in Table IV can be matched with the actual values for the factor listed in Table I.

TABLE IV
2-LEVEL AND 3-LEVEL CATEGORIC FACTORS

2-Level	Factor	
Level1	-1	
Level2	1	
3-Level	**Factor[1]**	**Factor[2]**
Level1	1	0
Level2	0	1
Level3	-1	-1

$$\begin{aligned}\text{Throughput} = {} & 1.182\text{E+06} - 33414.80 \cdot A \\ & +840.99 \cdot C - 46744.02 \cdot D_1 \\ & +19843.24 \cdot D_2 + 3.07\text{E+5} \cdot E \\ & +67257.11 \cdot F - 4591.44 \cdot G \\ & +5302.53 \cdot AC + 5222.30 \cdot AE \\ & +20803.76 \cdot AF + 3432.53 \cdot AG \\ & -17803.10 \cdot CD_1 + 8924.88 \cdot CD_2 \\ & +14576.42 \cdot CE - 7147.15 \cdot CF \\ & -4453.98 \cdot CG + 22387.70 \cdot D_1E \\ & -9267.77 \cdot D_2E + 15225.32 \cdot EF \\ & +22817.54 \cdot EG - 17968.38 \cdot FG \\ & +19241.48 \cdot A^2 - 74394.65 \cdot F^2 \qquad (1)\end{aligned}$$

Predictive Model for Latency

This subsection presents the results of DOE analysis with respect to latency. The results for latency did not produce a model that we felt adequately predicted the response. Figure 5 gives the normal plot for latency (notice the non-linear pattern to the data). Additionally, R^2 for the ANOVA on the significant factors for latency was 0.82.

We felt this value of R^2 provided less predictability than needed; in these cases, we can select alternate prediction

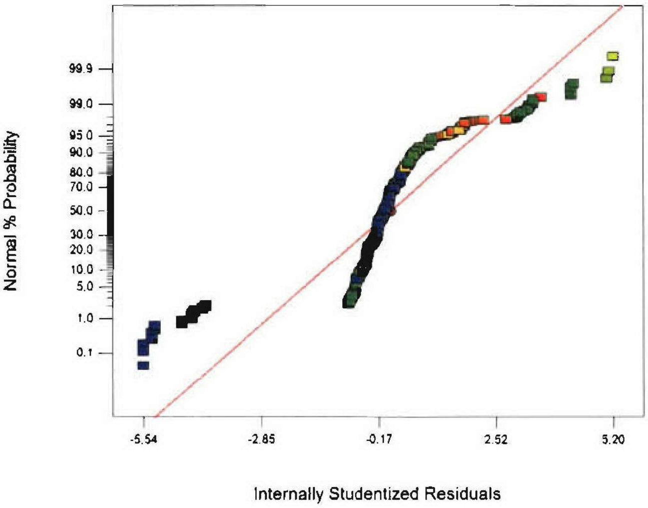

Fig. 5. Predicted Latency Normal Plot (R^2:0.82)

methods. Since the data in Figure 5 is highly clustered, we employed recursive partitioning on Selective Queueing, Frame Size, and Data Rate to produce a regression tree [19]. A regression tree is similar to a *decision tree*; predictions are made by "splitting" categories of data within nodes in such a way that they maximally reduce the variance. This technique is suitable for highly clustered predictions such as those we observed for latency. This tree provides a set of leaves (with specific parameter settings) that fulfill the latency requirements.

Figure 6 shows the regression tree produced by the statistical package (R). To make use of the tree you would single out those leaves that meet your latency requirements. From this tree the set of configurations can be determined by tracing the leaf node back to the root. For example, to achieve a latency of less than 6 ms there are two candidate leaves, 5.25ms and 5.38ms. The set of possible configurations for this goal is found by tracing back to the root of the tree. For 5.38ms, the Data Rate is 2 Mbs and the Frame Size is Medium. This process is repeated and a set of configurations that meet the requirement is generated. When combined with the regression model for throughput (or some other requirement like minimizing transmit power), we are able to reduce the set of possible configurations to those that best meet our communication requirements. The CR need now only select from the resulting set of configurations randomly or apply additional screening criteria.

Conclusions and Future Directions

In this paper, we present a methodology through which a cognitive radio would be able to dynamically reconfigure itself in response to changes in application needs or

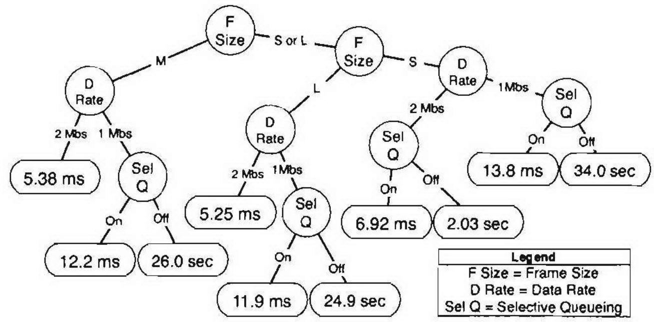

Fig. 6. Regression Tree for Latency

environmental conditions. In developing this methodology, we were able to create a regression model that accurately predicts throughput. We also derived a similar regression model for latency, but found this model less predictive. As a result, we produced a regression tree that is able to predict configurations that are able to meet latency requirements.

The dynamic nature of these CR systems leads us to other interesting questions. For example, it will be important to quantify the amount of time that a cognitive process can devote to computing an adaptive radio configuration, thus allowing one to characterize the types of processing can be done without negatively affecting communication. This line of research should also provide insight into what processing should be done in real-time, offline, or in the background. In addition to answering these questions, it is our intent to implement and evaluate the predictive models and techniques described in this paper on a fielded system (see MultiMAC platform [20]).

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