A GENETIC ALGORITHM APPROACH FOR THE DECISION-MAKING FRAMEWORK IN OPPORTUNISTIC RADIO

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ABSTRACT

Cognitive Radio (CR) introduces the idea of system awareness and intelligent adaptability to advance Software-Defined Radio (SDR). This has opened up an attractive aspect in the development of an efficient and intelligent optimization based on various soft-computing techniques. In this work, the focused radio concept is termed as Opportunistic Radio (OR), which is the narrower definition of CR considering solely the knowledge of spectrum awareness. The main concern of OR in here is the development of the decision-making framework and its approach. The method used here is the optimization based on Genetic Algorithm (GA). The paper presents the design of the OR decision-making framework with an implementation of multi-objective decision making using GAs.

1. INTRODUCTION

One of the major aspects in cognitive radio is the exploitation of artificial intelligent in order to bring Software-Defined Radio (SDR) into the next level, where the radio is aware of the environment and able to intelligently adapt its behavior using knowledge and past experience. A number of ongoing research focuses on the development of efficient optimization based on various soft-computing techniques. This work focuses on the narrower definition of Cognitive Radio (CR), where the environment knowledge is restricted to spectrum awareness. This radio concept is termed as Opportunistic Radio (OR). The main concern of OR in here is the development of the decision-making framework and its approach.

A decision making in OR consists of detecting the spectrum opportunities on the current environment and then re-configuring the radio device to exploit these opportunities and make opportunistic allocation decisions. The decision-making engine needs to take into account the universal context, which describes the radio environment, as an input entity. This engine also needs to be aware of the policies and profiles. Policies are sets of rules and action plans accordingly and profiles are the configuration settings describing information associated with each entity or application. The process involves the general understanding of these input entities through the machine understandable language.

The soft-computing method used here is the optimization based on Genetic Algorithm (GA). During the last two decades, GA has received considerable attention regarding their potential as a novel approach to multiple objective optimization problems. The multi-objective GA defines multiple fitness functions according to the specific objective functions. The algorithms evolve using genetic selection techniques to produce optimal solution.

The paper presents the design and development of the decision-making framework in OR together with the application of GA including the mapping of radio adaptation to artificial chromosome and defining fitness function to evaluate the chromosomes as part of the genetic search to find/select the best chromosome, which represents the preferred solution.

In section 2, the decision-making framework in OR is presented with the structure and discussion on each input entity. This section also covers the policy syntax and format used and the filtering mechanism. Section 3 discuss the GA approach for decision-making framework in OR using multi-objective optimization, followed by the conclusion in section 4.

2. DECISION-MAKING FRAMEWORK FOR OR

One of the main objectives in radio regulation is to avoid unwanted interference and degradation of signals of the primary users. In the case of OR, user's regulations are embedded in the spectrum policies and unlicensed or secondary users are expected to operate in varying geographical locations under different regulatory bodies and policies. Therefore, OR users must be able to dynamically select the best possible policy depending on the current situation.

Apart from that, spectrum policies of a given radio may change in several ways and vary in time. For example, during certain time of day, different spectrum policies or regulator policies may come in to effect. Also changing policy could occur according to the geographical location or space. In this case once policy domains are changed policies might change (for example roaming user between two policy domains such as cities, countries, continents etc.). Spectrum policies of the OR user also change according to the restrictions imposed by the spectrum owner (this can be the operator of the primary user in case of spectrum leasing or spectrum trading situations). Also spectrum access priorities between OR users may impose a change on spectrum policies of the current opportunistic user.

As a result of this dynamic nature, the amount of policy sets that can be applied to different environments in different scenarios grows in a combinatorial manner. Figure 1 summaries the general structure of OR decision-making framework.

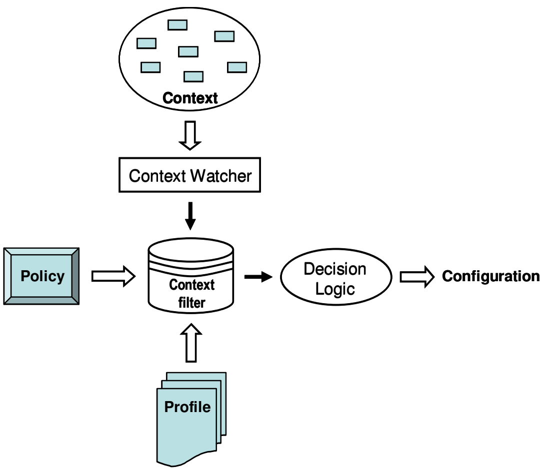

Figure 1: General Structure of OR Decision-Making Framework

As mentioned earlier, the OR decision-making engine needs to take into account several entities. These entities are inputs for the decision-making engine as shown in figure 1. The universal context is observed and obtained by the context watcher from available sensor devices. The three input entities are then passed through the context filter and operational context is produced. From the operational context, genetic search is done to propose the new configuration setting, which is suitable for the current situation.

2.1. Policy, Profile, and Context

This section introduces each input entity of the decision-making engine.

2.1.1 OR Policies

OR policies can be seen as a collection of rules defining a range of operational aspects. Policies can be set by various sources or actors such as user, regulator, operator, and market, whose requirements play a major role in policy determination. In different scenarios, different sets of policies are involved in the decision-making process. Example of OR policies are as follow:

- Authorization policies – based on the spectrum utilization identified by regulators in different countries/geographical locations
- Regulatory policies – defining the opportunities using the sensing parameters
- System policies – defines the manner of transmission that limits the level of interference perceived by other users and also determine mode of transmission according to the user service request

2.1.2. Profile

Profile in OR terminology is the configuration setting, which describes information associated with each entity or application. The following types of profile are considered here.

- User profiles define settings for applications and OR terminal associated with a single user. These profiles are different in case users are categorized into classes such as premium users, who are willing to pay for a higher cost in return for a guaranteed higher QoS and regular users, who receive best-effort services with lower cost. In general, user profiles include user preferences and personal service description such as QoS level, tariff preference, service personalization, and subscription requirement.
- Application Profiles store configuration settings for a distinct application or group of applications with common attributes. Application profiles assist the decision process since they define application requirements such as bandwidth request, minimum requirement for the transmission speed, minimum throughput, and allowed/maximum delay (for delay tolerant applications) and jitter.
- Terminal capability profiles are a subset of the device capability profiles and contain capability settings for the OR terminal. The profile includes parameters - that can be configured such as radio access options, transmission power range, terminal resources, protocol environment etc - and sensing services available to neighbouring OR terminal. Terminal capability profiles can be seen as a description of a control and status interface to the

OR functions since they define parameters that can be configured and services that can be used by the decision-making framework.

2.1.3. Context

Context in general is any information that can be used to characterize the situation of an entity. In OR terminology, it is a function of parameters describing the system environment and it is acquired by using sensors for the radio context information or from the network for higher layer context information.

In this work, the idea of context-aware system is adopted. Context-aware system is the system that has ability to dynamically adapt its behaviour based on the context of application and user.

2.2. Policy Syntax and Format

As mentioned, the decision-making process involves general understanding of the input entities. Ontology is employed in order to support the exchange of this information.

Following the literature, the technology to handle policies is developed based on Semantic Web ideas. There are a number of policy languages, which in general are categorized into those addressing access control and the ones that address resource management. Example of policy languages under consideration here are *PDL* [1], Ponder [2] and the DARPA-XG Policy Language [3].

The XG Policy Language (XGPL) is chosen to be used as a basis for describing OR policies. XGPL was developed as part of the U.S. Defence Advanced Research Project Agency (DARPA) neXt Generation (XG) radio development program, which is the first example that proposed a policy-based management framework for cognitive radios.

There are three basic constructs in building XG policy language framework: facts, expressions, and rules. Policies encoded in XGPL consist of a set of facts that are OWL (Web Ontology Language) [4] statements that describe the policy concept, and expressions that are used to define an opportunity, a usage description, or to define membership in a policy group. Rule constructs are used to specify processing logic for policies and they have the form of: *condition-implies-action*.

Policy rule consists of three elements: *the selector description* (filters policies to a specific environment), *the opportunity description* (specifies the conditions that spectrum is considered as unused), and *the usage constraint* description (specifies the behaviours of the cognitive radio when using spectrum opportunity). Figure 2 shows the XGPL policy structure.

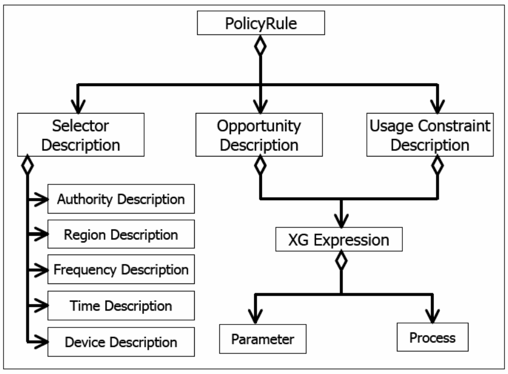

Figure 2: XGPL Policy Structure [3]

2.3. Filtering Mechanism

The next component in the proposed framework is the context filter. Several possible filtering mechanisms are investigated. The Concerned Value (CV) Algorithm is introduced in [5] as the context filter to evaluate the importance of specific contexts by gathering the information from pervasive applications and the context reasoner. Collaborative filtering or social filtering is a software technology that uses the idea of shifting from an individual to a collaborative method of recommendation. The basic mechanism of automated collaborative filtering (ACF) [6] is by using the average rating of each item of potential interest and form a similarity matrix. A subgroup of items is selected based on the popularity and interest.

Cased-Based Reasoning (CBR) is one artificial intelligence that allows the learning from past successes. CBR is a method that finds the solution to the new problem by analyzing previously solved problem, called cases, or adapting old solutions to meet new demands. Using CBR in filtering process therefore involves the learning about the policy from what it observes of its action and the information it has explicitly been told. In this case, the profiles and policies contain all the initial preferences, which are treated as knowledge for filtering engine. This information can be entered by the users or learned by the system observing the activities over time.

Comparing CBR with the ACF approach, which also looks at the behaviour of other users (policies in this case) who are considered similar however their associated feathers are semantically weak, CBR has the benefit. [7] discusses the CBR approach to collaborative filtering and demonstrated the success of using semantic ratings in that.

In this work, case-based and rule-based reasoning is initially implemented as for the simplicity reason. More sophisticated approach could be introduced in later stage to advance the system. The main purpose here is to be able to narrow down the search for the decision making in order to offer the optimal solution.

As illustrated in figure 1, universal set of parameters forms the context. This context is then managed and filtered by using each policy and profile in order to achieve the so called operational context, which describes the possible options (opportunities). Finally, the decision logic determines the optimum operational context to obtain the most advantageous opportunity by offering new configuration setting.

In the next section, the proposed multi-objective decision making, using GAs is described including the process for the optimization using GAs techniques adapted here.

3. GENETIC ALGORITHM APPROACH FOR OR DECISION MAKING FRAMEWORK

During the last two decades, GAs have received considerable attention regarding their potential as a novel approach to multiple objective optimization problems. The inherent characteristics of the genetic algorithms demonstrate why genetic search may be well suited to multiple objective optimization problems. In current research activities, [8] of Virginia Tech describes the cognitive decision making process using GAs to solve the multi-objective optimization problem faced in the cognitive radio.

The genetic algorithms are essentially a type of meta-strategy of solutions, when applying them to solve multi-objective decision making problems, it is necessary to define each of their major components, such as encoding methods, recombination operators, fitness evaluation, and selection etc., to obtain effective implementation to the problem.

Refer to the framework proposed in figure 1, once the universal context is narrowed down and the operational context is proposed, the decision-making process is operated to find the optimum configuration settings for the opportunities usage. In this work, the approach utilised here involves GAs in solving the optimization problem. The process is illustrated in figure 3 and the following procedures show the steps of solving the optimization problem using the genetic algorithms.

3.1. Encoding

The initial population is generated from the achieved operational context. The solutions are encoded into a chromosome. Encoding a solution into a chromosome is a key issue in GAs. The issue has been investigated from many aspects including mapping characters from genotype to phenotype space when chromosomes are decoded into solutions. According to what kind of symbol is used as alleles of a gene, the encoding methods can be classified as follows:

- Binary encoding
- Real-number or Value encoding
- Integer or literal permutation encoding

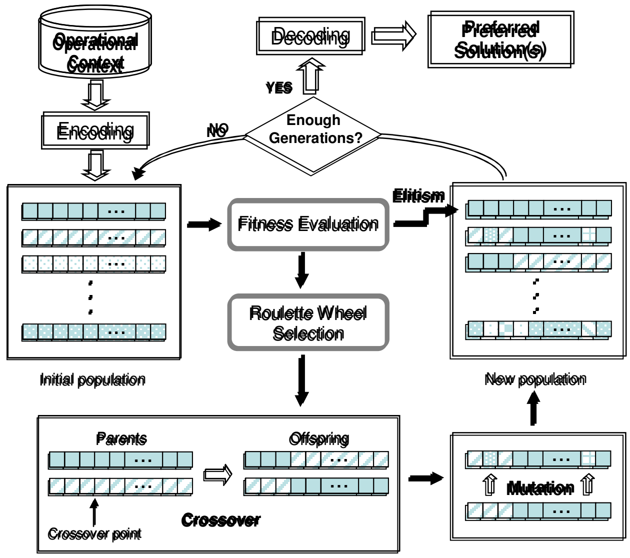

Figure 3: GA Based Decision Making Tool for OR

In this work, a combination of binary and real-number encoding technique is used to represent solutions. The chromosome consists of three sections: spectrum opportunities, configurations, and OR policies. The spectrum opportunities section defines the available bandwidth. The configurations section includes parameters controlling the radio operation such as the transmitter power, data rate, etc. As for the encoding used here, the spectrum opportunities and policies are mapped using binary encoding technique. Whereas, the terminal and base station configurations are mapped using real-number encoding methods. A typical chromosome proposed for the GA is shown in figure 4, where the crossover operation in GA is discussed.

3.2. Fitness Function

The fitness function is then used to calculate the fitness value for each chromosome, providing the measurement of performance with respect to solution encoded in the chromosome.

A single-objective optimization problem is usually given in the following form:

$$\max z = f(x) \qquad (1)$$

subject to $C_i(x) \le 0$ for i = 1, 2, …, m

where $x \in R^n$ is a vector of n decision variables, *f(x)* an objective function, and *Ci(x)* inequality constraint *m* functions which form an area of feasible solutions. The feasible area in decision space is defined by the set S such that:

$$S = \left\{ x \in R^n \mid C_i(x) \le 0, i = 1,2,...,m, x \ge 0 \right\} \quad (2)$$

Without loss of generality, a multiple-objective optimization problem can be represented formally as follows:

$$\max \begin{Bmatrix} z_1 = f_1(x) \\ z_2 = f_{21}(x) \\ .... \\ z_q = f_q(x) \end{Bmatrix} \quad (3)$$

subject to $C_i(x) \le 0$ for $i = 1, 2, \ldots, m$

where z_1, z_2 ... z_q are the objective functions and sometimes, the multi-objective problem is graphed in both decision space and criterion space. *S* is used to denote the feasible region in the *decision space* and Z is used to denote the feasible region in the *criterion space.*

$$Z = \left\{ z \in R^q \middle| z_1 = f_1(x), z_2 = f_2(x), \ldots z_q = f_q(x), x \in S \right\} \quad (4)$$

where $z \in R^q$ is a vector of values of q objective functions. In other words, *Z* is the set of images of all points in *S*. Although *S* is confined to the non-negative orthant of R^n, *Z* is not necessarily confined to the nonnegative orthant of R^n.

In principle, multi-objective optimization problems are very different from single-objective optimization problems. In the single objective case, one attempts to obtain the best solution, which is absolutely superior to all other alternatives. In the case of multiple objectives, it does not necessarily exist a solution which is the best with respect to all the objectives because of incommensurability and conflict among objectives. A solution may be the best in one objective and worst in other objectives. Therefore, usually there exist a set of solutions for the multiple objective case which cannot simply be compared with each other. These solutions are called *non-dominated* solutions or *Pareto optimal* solutions; no improvement in any objective function is possible without sacrificing at least one of the objective functions. As a result, general expectation for a decision making process can be either to obtain a compromised or preferred solution or identify all non-dominated solutions.

Fitness assignment mechanisms have been studied extensively during the past decade and several methods have been suggested and tested. These methods can be classified as follows:

- Weighted-sum approach
- Vector evaluation approach [9]
- Pareto-based approach [10]
- Rank-based approach [11]
- Compromise approach
- Goal programming approach

Each method has its own advantages and disadvantages when applying to multi-objective decision making problems, therefore a detailed study is required to identify the most appropriate technique to satisfy the objectives of the OR policy framework.

In this study, several fitness functions will be defined to consider different objectives, for example to maximize spectral efficiency, minimize signal power and interference etc. The specific knowledge about the OR framework is used to define the fineness function.

3.3. Elitism

Elitism is a selection method, which retains the best chromosome(s) at each generation and carries over to the next population. This method guarantees that the chromosome(s) with best fitness value(s) will not be lost during the selection process. Here, in each generation two chromosomes with best fitness values are selected and forwarded to the new population.

3.4. Selection process and GA operations

This step is performed to produce the offspring from the selected parents in order to complete the new population.

For the selection process, there are several existing methods as follow:

- Fitness-proportionate selection: Roulette Wheel Sampling and Stochastic Universal Sampling
- Boltzmann selection
- Rank selection
- Tournament selection
- Steady-state selection

In this work, the fitness-proportionate selection using Roulette Wheel Sampling [10] is implemented. By using this method, the chromosome with higher fitness value is given larger slice in the "roulette wheel" leading to higher possibility of being selected.

At this stage, two chromosomes are selected to be the parents. They are then passed to the GA operations called *crossover* and *mutation*, in which the offspring is produced and forwarded to the next generation.

For the crossover operation, two new chromosomes are created by swapping section(s) of genes from parents by which the position is determined by crossover points. Figure 4 illustrates the crossover process proposed here. As mentioned, the chromosome structure proposed here consists of three sections representing spectrum opportunities, configurations, and policies. Three crossover points are randomly generated, one for each section. Example for the process, which also shows the crossover results, can be seen in figure 4.

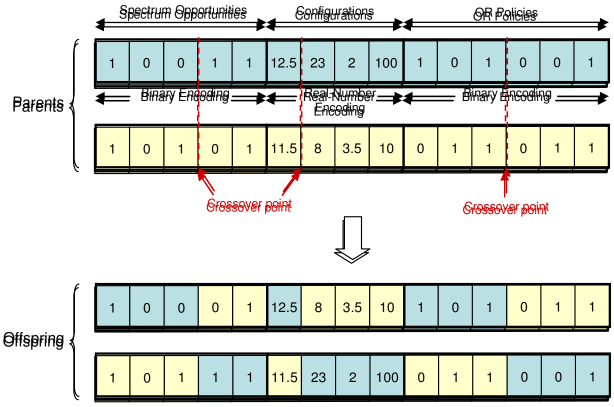

Figure 4: Crossover Operation in OR Decision Making

In the mutation operation, random modification is done to the randomly selected gene(s). The crossover and mutation probability are set to control how often the crossover and mutation are performed.

This procedure is repeated until the number of chromosomes in the next generation is met.

3.5. Termination

As seen in figure 3, the search continues until the termination criterion is met either when the convergence is achieved or the maximum number of generation is reached. Finally the best chromosome is selected and decoded to obtain the preferred solution.

4. CONCLUSION

This paper has introduced the proposed design of the OR decision making framework, which includes the discussion on each component and the procedure. The focus of the decision making engine proposed here is the implementation of multi-objective decision making using Genetic Algorithms to provide the optimum solution for the spectrum utilization. With the implementation of GAs, beside the multiple objective optimization benefit brought into the decision making, the system also benefit from fast and low cost search, which support real time application. It also simplifies the search of a large space with complicate problems.

5. ACKNOWLEDGEMENTS

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