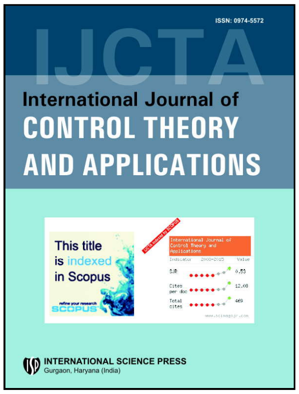

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A PMOGA Based Approach for Efficient Spectrum Utilization in Cognitive Radio

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Abstract: Cognitive radio being in developing stage has many problems yet to be addressed. Problem of spectrum utilization is one of them. The application of genetic algorithm is a viable but not an optimal choice as the spectrum utilization problem consists of multiple objectives. For the same reason this paper presents a proposed parallel multi-objective genetic algorithm using NSGA II to address spectrum utilization problems of cognitive radio, where the main purpose is to minimize the bit error rate and interference whilst achieving throughput maximization in feasible amount of time. The paper then compares the results of parallelization by varying the number of processors.

Keywords: Cognitive Radio, Multi-Objective Genetic Algorithm, Spectrum Utilization

1. INTRODUCTION

Cognitive radio is a technology in wireless environment, which has the ability of sensing and accessing the spectrum in an opportunistic way, to detect environmental changes and successfully adapt itself to the environment instantly. The principle that cognitive radio mainly works under is popularly known as dynamic spectrum access, where the intention is to use spectrum holes or the vacant frequencies assigned specifically to the primary users. Authors in [1] have given elaborative explanations of the issues in cognitive radio categorizing them under physical (PHY), Media Access Control (MAC) layer and Network layer. Physical layer basically deals with responsibilities viz. Spectrum Sensing, Spectrum Access and Environmental Learning.

The requirement for sensing the spectrum is the information regarding the availability and usage of the concerned primary user along with maximizing the efficiency of the radio spectrum and reducing the interference whilst communicating. A variety of spectrum sensing techniques are available which has been classified as direct spectrum sensing, indirect spectrum sensing and cooperative spectrum sensing. Spectrum access has to deal with the "how to access" part, and there are two models viz. Opportunistic Spectrum Access (OSA) model and Concurrent Spectrum Access (CSA) model, the main difference comes in tolerance of interference among the two, OSA model works under zero interference policy whereas CSA model only needs the interference to be below a particular threshold value. Where proper information regarding the input is unavailable in a radio environment for a decision making problem, then, the information is statistically estimated, and the ultimate purpose is to gain knowledge from external and internal radio environments and use that knowledge to infer decisions regarding the access of spectrum holes to perform wireless communications in cognitive radio networks (CRNs) in a successful manner.

Issues dealt by MAC layer can be classified as scheduling of spectrum sensing, Spectrum Aware MAC, and coordinating spectrum-access. Scheduling of spectrum sensing refers to determination of spectrum sensing time and data transmission time in an optimal manner. The main targets of the protocols under spectrum aware MAC are to sense the spectrum accurately, timely and maintaining the Quality of Service of the cognitive radio transmission. The coordination of the spectrum-access category comprises of protocols whose main focus is to control the operations of sensing the spectrum and accessing the spectrum.

The protocols under the category of spectrum-aware routing, concentrates on managing the routing procedure dynamically based on spectrum availability and spectrum allocation to achieve minimum interference to primary user along with maximum transmission by the users [1].

1.1. Geneticalgorithm

Genetic algorithms are suitable to explore potentially huge search spaces and address intractable problems. Genetic algorithm accepts uncertainty, partial truth and approximation to provide a set of approximate solutions [1,9]. Genetic algorithm requires a huge amount of time to provide the approximate solution by considering all the parameters specified by quality of service (QoS). It is also clear that while addressing the spectrum utilization problem in a cognitive radio, it is associated with more than one objective which leads to a multi objective problem. Hence, a simple genetic algorithm will not be able to provide the solution in a feasible amount of time. So, a Multi – objective Genetic Algorithm (MOGA) can be used to find the tradeoff solutions. But the convergence time for a MOGA is un-realistic, so it is very difficult to use it in practical. Hence, in this paper we propose a Parallel Multi-objective Genetic Algorithm (PMOGA), by parallelizing the widely used multi objective genetic algorithm NSGA-II, which can address the spectrum utilization problem in a reasonable amount of time.

The rest of the paper is organized as below, section II discusses on Multi-objective Genetic Algorithm. Proposed PMOGA is discussed in section III. Section IV and V presents the result analysis and conclusion.

2. MULTI-OBJECTIVE GENETIC ALGORITHM (MOGA)

Multi-objective optimization deals with solving optimization problems which involve multiple objectives. In single objective optimization we get only one solution where as, in case of a muti objective optimization we get a tradeoff solutions as the objectives are contradictory to each other.The efficacy of the traditional optimization methods depend on the discritization of the search space and the shape of the pareto front. Genetic algorithm can be a suitable tool to get the solution as it has the ability [2,3,8] to find multiple optimal solutions in single run.

Genetic algorithms has been a popular heuristic approach for MOOP as they have the below characterstics:

- It has an ability to search simultaneously in different regions of solution space, to find a diverse set of solutions for difficult and complex problems with non-convex, discontinuous and multi-modal solution spaces.
- The crossover operator of genetic algorithm can exploit structures of good solutions in unexplored part of Pareto front.
- It is not required by the user to prioritize the scale and weight in majority of multi-objective genetic algorithm.

2.1. Application of Multi-Objective Genetic Algorithm in spectrum utilization in Cognitive Radio Network

Cognitive radio network consists of primary users or licensed users and secondary users or unlicensed users, the purpose of the dynamic spectrum allocation is to give the secondary users access to the primary user's spectrum to use it simultaneously without interfering with the primary user. What a secondary user needs to do, is, to find out, by conducting a localized search, the spectrum holes and transmit [4].

In cognitive radio environment, prime requirement is quality of service, as a result, there is a time constraint to determine a decision. For this reason, genetic algorithm is a very suitable, but to address multiple objectives, with the time constraint in decision making, multi-objective genetic algorithm suits best because of its ability to search simultaneously in different regions of solution space, to find a diverse set of solutions for difficult and complex problems with non-convex, discontinuous and multi-modal solution spaces. While dealing with the spectrum utilization problem it is mainly associated with two objectives they are minimization of bit error rate, minimization of interference, and maximization of the data throughput. Bit error rate in each link as a measure of quality in terms of number of errors each bit encountered, and is dependent upon many factors, bandwidth, symbol rate, transmit power. Throughput represents the processing speed of the system, that is, at a given time how much information is being processed by the system. As a result, increasing the throughput would in turn mean, improving the system. System throughput degradation is caused by bit error rate and due to the same reason, the bit error rate should be maintained at some acceptance level [5]. Most of the shared spectrum environments share a common problem, interference, so does the cognitive radio environment. Minimization of interference always gets higher priority when the spectrum is to be utilized by the users, and to get high throughput and less error rate, minimization of interference is necessary [5].

3. PROPOSED PARALLEL MULTI-OBJECTIVE GENETIC

3.1. Algorithm for Spectrum Utilization

As multi-objective genetic algorithms are more flexible and easy to use for simultaneous optimization of many conflicting objectives with respect to traditional mathematical programming techniques, so, they are more popular in many applications involving multi-criteria. Multi-objective genetic algorithm takes more time for doing the fitness evaluation operation and also to converge to the real Pareto front. The use of parallelism is a solution to this as it can give results in a reasonable amount of time. Parallel Multi-Objective Genetic Algorithms (PMOGAs) are attractive mainly due to the following reasons:

- They can take advantage of memory to solve complex problems. Hence by this the efficient memory utilization.
- They allow the usage of large population size.
- They trend to improve the population diversity.
- Reduces the probability to get trapped in local optimal Pareto front.

The main problem is the parallelization of the selection operator, where global information is required to determine the relative performance of an individual with respect to all others in the current population. There are many parallel models available, out of which, in this particular paper, we are adopting the Master-Slave model.

Proposed Algorithm:

Randomly generate the population

Fitness calculation of each individual

WHILE (Stopping Criteria is met) DO

Divide the population equally among the processors by making processor 0 as master processor.

Fitness calculation of *n* individual (POP / NP) by the assigned processors

Collection of *n* *POP/NP fitness values from all processors by master processor.

Master Processorregulates Pareto Front current (t), updates Pareto Front known and assigns rank if necessary.

Master Processor accomplishes Niching operation.

Master Processor exhibits selection operation.

New population is created by applying crossover and mutation on master processor to generate new population.

ENDWHILE

3.1. NSGA II

In multi-objective genetic algorithms there are cases when multiple solutions for multiple objectives cannot be compared and said to better than each other with respect to the objectives as both the objectives are equally

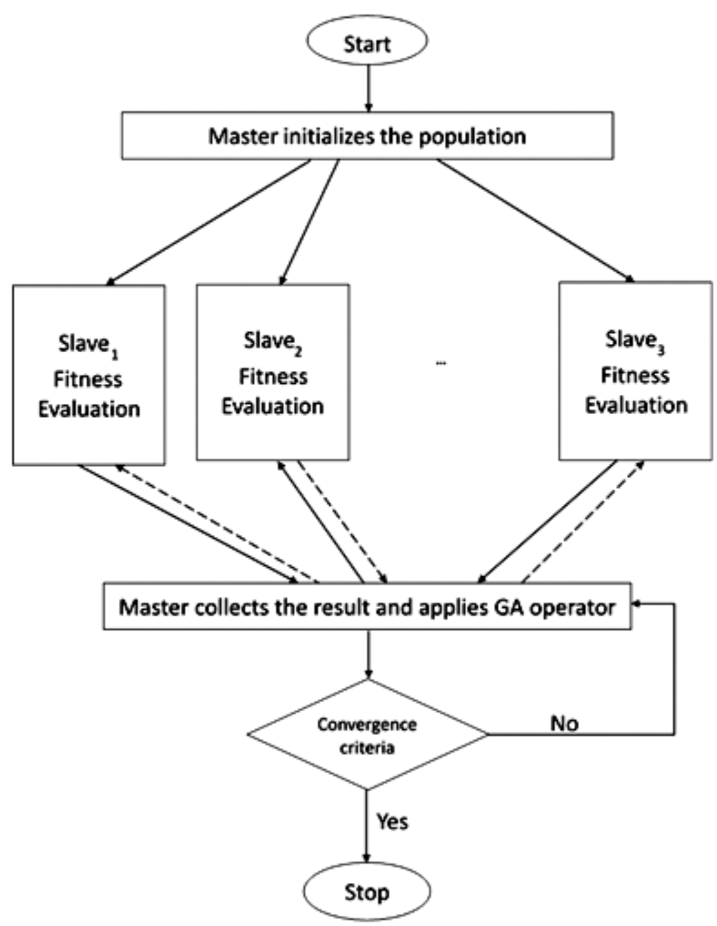

Figure 1: Steps of Master-Slave Model

important, the solution thus achieved comprising both the solution is known to be the non-dominated solution. Non-dominated sorting genetic algorithm-II (NSGA-II) is one widely accepted algorithm based on non-dominated approach, as it has the capability to find better spread of solutions and sustain better convergence, near the Pareto optimal front, however the main attraction of NSGA-II is its non-utilization of sharing function approach which in turn waives of the requirement of providing a sharing parameter and comparatively a fast non-dominated sorting approach [6].

4. IMPLEMENTATION AND RESULT ANALYSIS

4.1. Chromosome Representation

There are mainly two approaches for rule generation in genetic algorithms. The first one is named Michigan approach, in which each single rule is coded in form of one chromosome, and the rule base or the collection of rules is represented by the entire population of chromosomes, and the other one is named Pittsburgh approach, where a collection of rules are coded as one chromosome, which means a whole rule base is encoded in each chromosome, in this approach new combination of rules are provided by the crossover operation and new rules are created by mutation [7]. In this paper, Michigan approach is being used.

So let us assume there are m labelled instances represented by $Y_{q=(}Y_{q1,\ldots,}Y_{qn)}$, $q = 1,2, \ldots, m$, wherein Y_{qi} represents the value of i^{th} feature in the q^{th} instance. Now, let Q_{ALL} be the set of given m instances, $Q_{ALL} = Y_1, Y_2, \ldots, Y_m$. The set of given n features is denoted by $FE_{ALL} = fe_1, fe_2, \ldots, fe_n$ where fe_i is the label of i^{th} feature. Let FE and Q be the set of selected features and set of selected instances, respectively, where $FE \subseteq FE_{ALL}$ and $Q \subseteq Q_{ALL}$.

att_1	att_2	...	att_n	Is_1	Is_2	...	Is_m

Figure 2: Chromosome representation in PMOGA

We denote the reference set $IS = (FE, Q)$ is coded as binary string of length $(m + n)$ as in equation (1). The pictorial representation is shown in Figure 2.

$$S = att_1 att_2 \ldots a_{ttn} Is_1 Is_1 Is_2 \ldots Is_m \tag{1}$$

Where, the value of att_i and Is_q value is either 0 or 1 depending on its prescence. The feature set FE and the instance set Q are obtained by decoding the string IS as in equation (2) and equation (3).

$$FE = \{ fe_i \mid att_i = 1, i = 1,2,\ldots,n \} \tag{2}$$

$$FE = \{ Y_q \mid Is_q = 1,2,\ldots,m \} \tag{3}$$

The main objective of this paper is to achieve minimization of bit error rate, minimization of interference, and maximization of the data throughput.To do the Population Adaptation genetic algorithm, to bias the generation which was first initialized, towards the optimal decision which was found in the previous genetic algorithm cycle, seeding is performed based on the environment variation information, on the initial generation with high scoring chromosomes from the previous run [4]. The advantage of population seeding is in faster genetic algorithm convergence time which is needed to provide acceptable radio transmission configurations. Similarly for Variable Adaptation the secondary users, to reduce search space, set up proper variable ranges based on the statistical data generated from the knowledge gained from previous experiences.

PMOGA NSGA II algorithms are implemented on a multi-core system, core i7 with 8 cores, each of 1.6 GHz, 4 GB RAM, under Linux operating system. For the communication between the processors, MPICH library is used. The parameters of the PMOGA are explained in Table - 1. At last the result is analyzed between

1, 2 and 4 processor implementations. The objectives that are to be optimized simultaneously are viz. minimization of bit error rate, maximization of throughput and minimization of interference. The evaluation of 1, 2 and 4 processor implementations with different secondary user demands is performed in four cases of 192 kbps, 256 kbps, 320 kbps, and 352 kbps.

Table 1
Parameter setting for PMOGA

Processor	1,2,4
Population Size	200
Crossover Probability	0.8
Mutation Probability	0.1

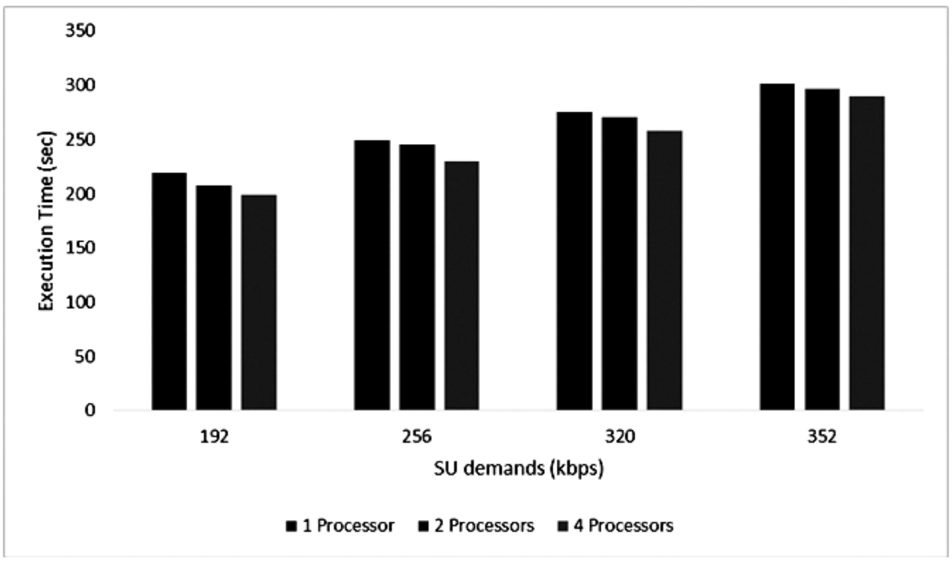

Figure 3: Execution vs SU demands graph

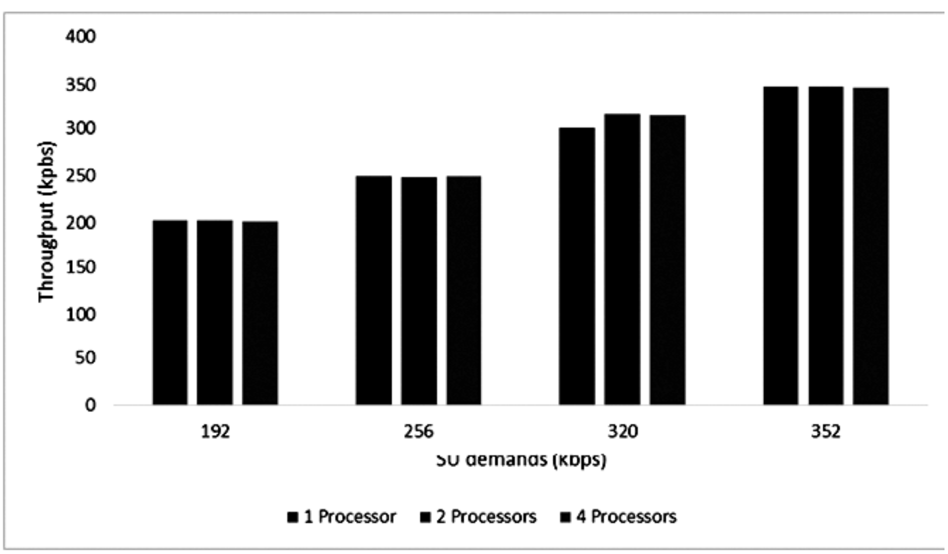

Figure 4: Throughput vs SU demands graph

Table 2
Summary of two graphs

SU Demands (kbps)	*Number of Processors*	*Execution Time (sec)*	*Throughput (kbps)*
	1	219.5	203
192	2	208	203
	4	199.1	202
	1	249	250
256	2	245	249
	4	230.3	250
	1	275	300
320	2	270.2	319
	4	258.28	318
	1	302	348
352	2	297	348
	4	290.1	347

4. CONCLUSION

In this paper we presented a parallel method to handle the multi objective spectrum utilization problem. It is clear from the experiment that by parallelizing the NSGA II we are able to explore the entire search space in less amount of time without compromising with the throughput.

REFERENCES

[1] S. Mishra, S. S. Singh, B. S. P. Mishra, and P. K Panigrahi, "Research on Soft Computing Techniques for Cognitive Radio," International Journal of Mobile Computing and Multimedia Communications (IJMCMC), Vol. 7, No. 2, pp. 53-73, 2016.

[2] H. Ishibuchi, I. Kunwajima, Y. Nojima, " Multi-objective evolutionary algorithms for knowledge discovery from databases,"Evolutionary Multi-objective Rule Selection for classification rule mining, Springer, 2005.

[3] Z. Jin-hua, " Multi-objective Evolutionary Algorithm and its Application",Science Press, 2007.

[4] S. Chen, T. R. Newman, J. B. Evans, and A. M. Wyglinski, " Genetic algorithm-based optimization for cognitive radio networks,"2010 IEEE Sarnoff Symposium, Princeton, NJ, pp. 1-6,2010.

[5] I. Al Qerm and B. Shihada, "Adaptive multi-objective Optimization scheme for cognitive radio resource management,"2014 IEEE Global Communications Conference, Austin, TX, pp. 857-863, 2014.

[6] K. Deb, A. Pratap, S. Agarwal and T. Meyarivan, "A fast and elitist multiobjective genetic algorithm: NSGA-II," IEEE Transactions on Evolutionary Computation, Vol. 6, No. 2, pp. 182-197, 2002.

[7] D. Rutkowska, "Neuro-Fuzzy Architectures and Hybrid Learning,"Springer-Verlag Berlin Heidelberg, 2002.

[8] B. S. P. Mishra, A. K. Addy, R. Roy, and S. Dehuri, "Parallel multi-objective genetic algorithms for associative classification rule mining", Proceedings of the 2011 International Conference on Communication, Computing & Security (ICCCS 11), Rourkela, Odisha, India, pp. 409-414, 2011.

[9] B. S. P. Mishra, and S. Dehuri, "A Critical Survey of Single- and Multi-Objective Parallel Genetic Algorithms" The IUP Journal of Computer Sciences, Vol. V, No. 1, pp. 52-87, 2011.