Improving efficiency of Genetic Algorithm Based Optimizer for Cognitive Radio

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Problem considered

- Given a SDR with a set of configurable parameters, user specified QoS requirement and Environment parameters affecting the performance.

- Find the configuration for SDR that best meets the user's QoS requirement.

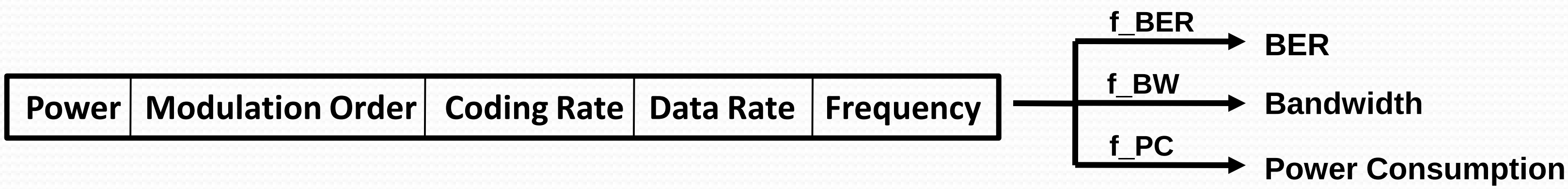
Problem is not trivial because …

- The problem involves multiple inter-dependent objectives to optimize in QoS.

- The search space can be very large, so it can be impractical to use conventional search algorithms.

Genetic Algorithms (GA) for multi-objective optimization

- Model the physical radio system as biological organism.
- Represent configurable parameters as genes in Chromosome of GA.



- Set the objective functions to calculate value of each objective in QoS.
- Initialize with a relatively small population of such chromosomes and analyze populations through generations, to find individuals that are non-dominated in terms of multiple objectives.
- All non-dominated individuals form the optimal solutions that lie on pareto front.

Genetic Algorithms (GA) for multi-objective optimization

- Difficulty with GA processing:
  - Not suitable for applications where immediate response from system is required (of the order of milliseconds) due to inherent processing time of GA.

Advanced GA techniques to improve performance

- There are advanced GA techniques to enhance the performance of genetic algorithms in terms of accuracy and time.
  - For accuracy, niching can be used to maintain population diversity throughout the GA to find global optimum.
  - Parallel Genetic Algorithms can be used to exploit parallel processing for improving performance.
  - Biasing the initial population using domain knowledge and using case-based initialization/heuristics techniques for GA.
- Still difficult to incorporate due to involved GA processing.

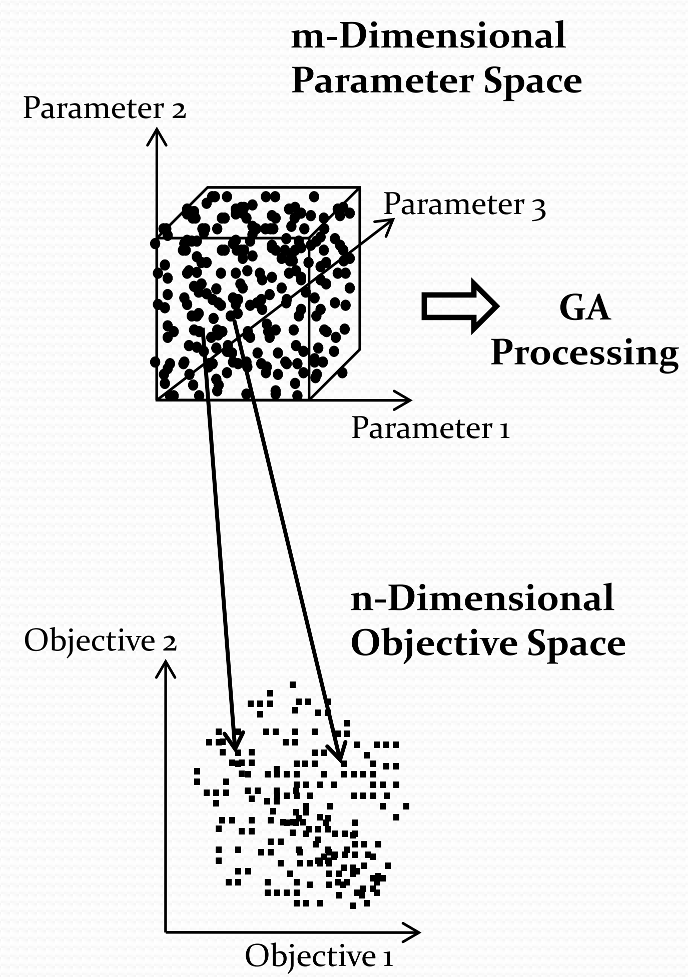
Proposed Approach

- The key idea is to store the optimal solutions from the GA for given environment parameters and use them subsequently even if the environment parameters change.

- The approach suggested exploits the observation that there is an overlap between the optimal solutions of GA when there is change in environment parameters.

Parameter Space & Objective space

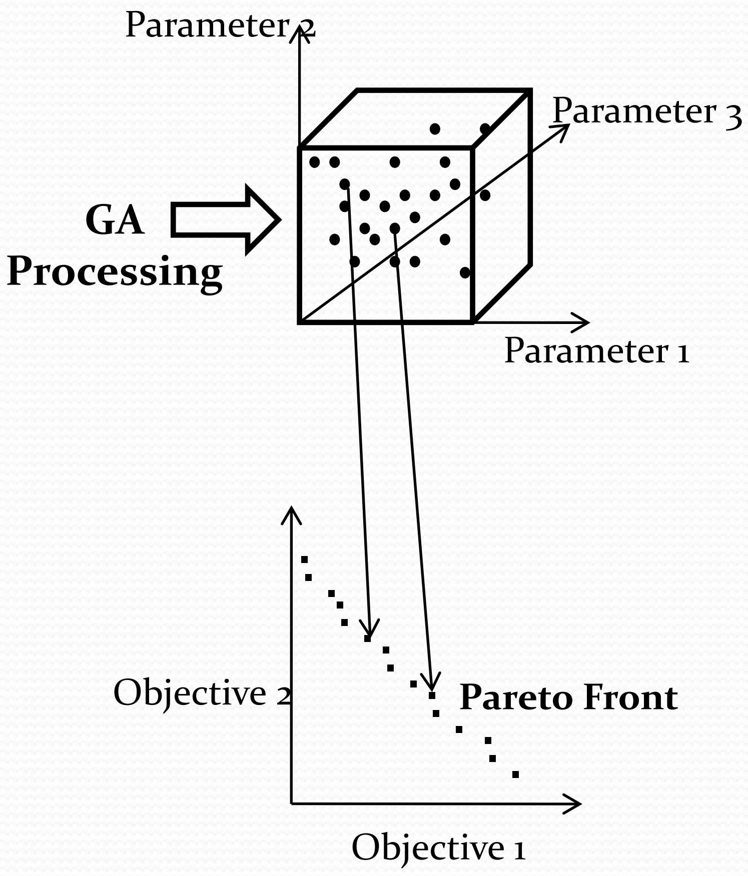
- Parameter Space: Formed by configurable parameters of SDR.
  - e.g. Tx Power, Modulation Order, Coding Rate etc.
- Objective Space: Formed by objective parameters in QoS.
  - e.g. BER, Bandwidth etc.
- Objective functions map parameter space to objective space.
- Objective functions use environment parameters’ values.



Optimization process (**Step-1**)

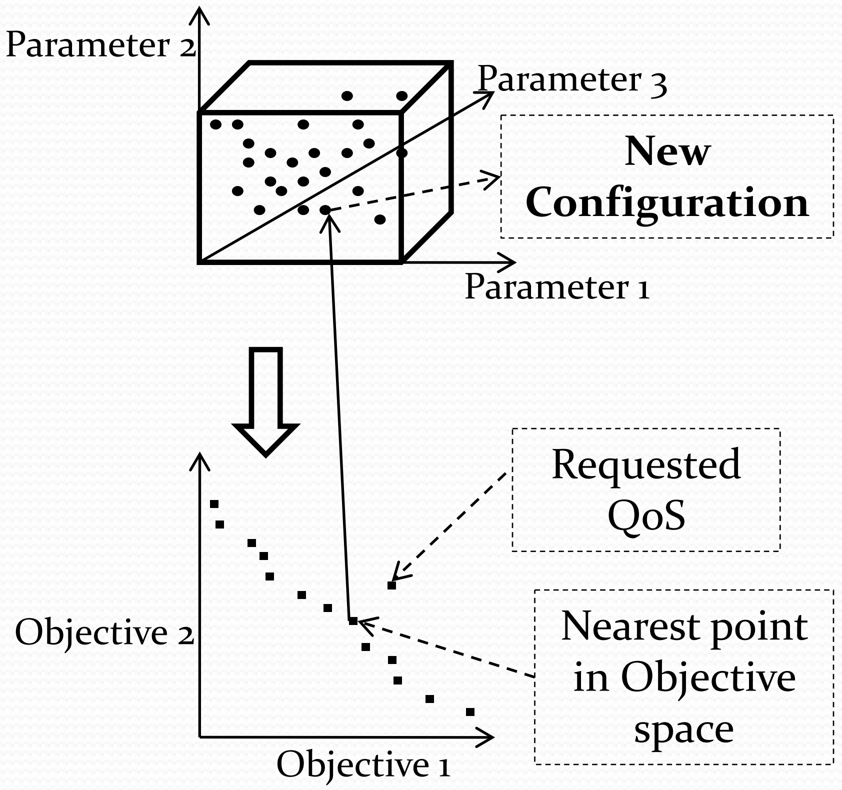
- Get Non-dominated Set using GA processing
  - Non-dominated set has configurations such that no configuration is outperforming the other in terms of all objectives.
  - e.g. the vector (3,4) is not dominated by (1,6) and vice versa.

    While (3,4) will be dominated by (6,7) for a maximization problem.



Optimization process (**Step-2**)

- Get new configuration from Non-dominated set
  - Found by taking the individual from parameter space that is mapped nearest to requested QoS in objective space.



Simulation parameters

SDR's configurable parameters

Knob	Values	Count
Modulation Order for PSK	2,4	2
Coding Rate	1/2, 1/3, 3/4	3
Data Rate	10000, 20000, 30000 bits per second	3
Transmit Power	-100 to 10 dBm (at 0.04 dBm steps)	2751
Transmit Frequency	900 to 920 MHz (at 1 KHz steps)	10001

GA parameters

Parameter	Values
Population Size	4000
Non-Dominated Set Size	5600
Mating Pool Size	2400
Generations	6
Crossover	0.98
Mutation	0.02

Parameter Space Size= 495229518

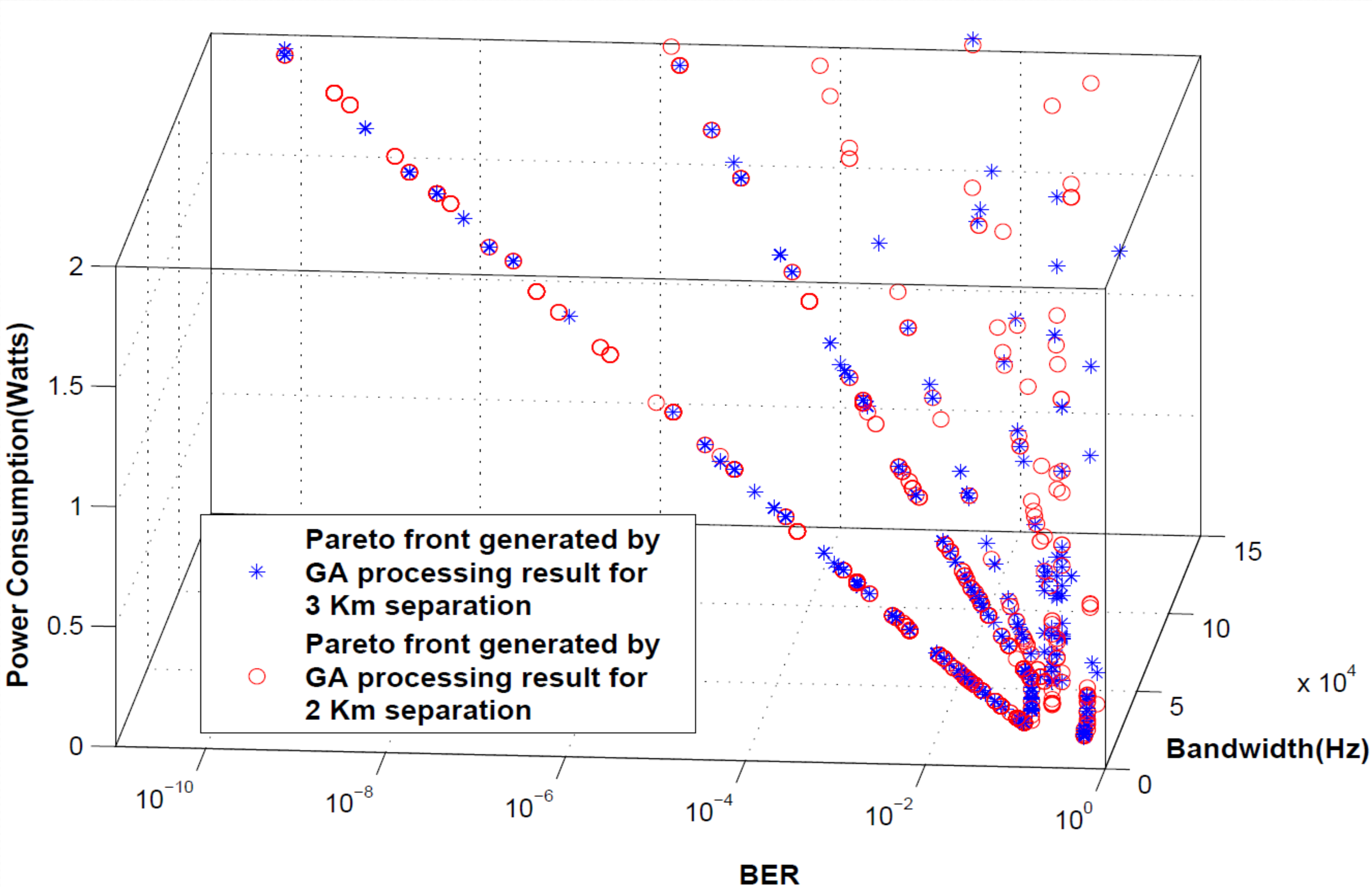
Simulation parameters

- Objective space parameters are
  - BER, Bandwidth and Power consumption

- Environment parameter is SNR at receiver.

- A line of sight communication is assumed between transmitter and receiver.

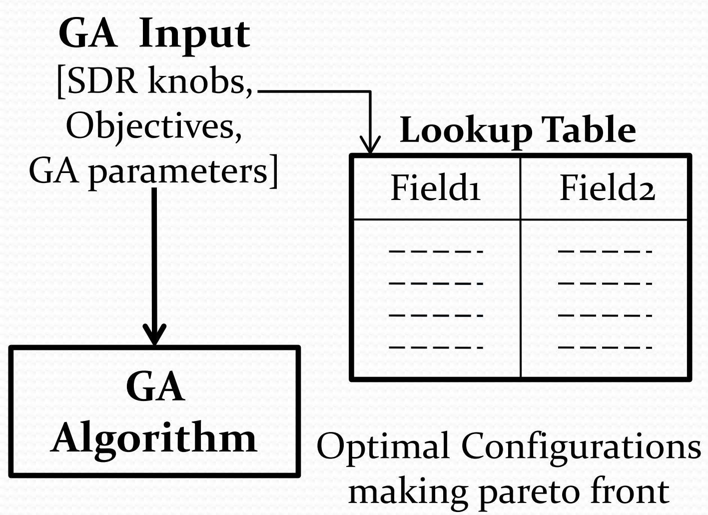
Observation



Proposed Solution and Results

- Make step-1 of process as offline process.
  - i.e. Calculate non-dominated solutions set in advance and store in a lookup table.

- The step-2 takes care of change in environment parameters' value.



Execution Time Comparisons

Population Size	Using GA (Step-1 & Step-2)	Using Proposed approach
4000	5880.6 Seconds	6.144 Seconds
400	67.22 Seconds	0.1593 Seconds
50	456.8 Milliseconds	48.12 Milliseconds

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Thank You

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