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# Multi-objective function formulation to evaluate operating parameters fitness for sharing and scalability

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**Abstract**

A new era of advanced information technology allows multiple service operators to potentially use incompatible radio technologies and shared bands but the systems require dynamic management and coordination. To optimize resources via qualitative services and reduced network latency require strategic approach. Utilizing spectrum systematically while managing operating parameters to provide minimal trade off between efficiency and effectiveness is our concern. Popular internet apps have distinct radio resource allocation signatures, which necessitate cooperative optimization to deliver higher throughput (efficiency) and fairness (effectiveness). Wireless system (LTE and Wi-Fi networks) performance is evaluated for low-power consumption and higher network-utility delivery. While handling selected parameters to prevent throughput starvation and latency increase, convergence of fitness in parallel optimization is evaluated with genetic algorithm. Crossover is implemented adaptively for instance-based learning. Selection of parameters and evaluation with formulated multi-objective

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function facilitate cooperative optimization. The technique offer mutual benefit of mobility, flexible access and guaranteed adaptation with steady-state procedures. Cooperatively tuned crossover and mutation effect learning, population searching and parameter selection to breed more parallel optimization. New population (with highest fitness) identified is evaluated for fitness to achieve adaptation for users to trigger required scaling.

# 1 Introduction

Optimization has major impact on adaptive systems and parameters that impact performance of wireless systems are either transmission level controlled or environmentally sensed. With multiple service operators and distinct radio resource allocation signatures in information technologies (IT), utilization of spectrum typically depends on signal-to-noise ratio (SNR) potentially used to make accurate decisions. Policies and constraints specific to radio access technologies (RATs) aggravates throughput starvation, time delays and increased latencies (Huawei, 2014). In the context of mobile communication, latency is the response time of an HTTP request, and bit error bottleneck is associated with bandwidth usage, carrier frequency and implemented modulation techniques. Zhao (2018) proposed a noble client-centric technique of pre-fetching HTTP requests in mobile apps as an approach for minimizing the network latency. Current reports and observation shows that a majority of mobile users prefer abandoning a transaction or even delete the app if the response time exceeds 5-10s (AppDynamics, 2014). Also, existing incompatible radio technologies endanger convergence between the multiple service operators. With diverse technologies of LTE, Wi-Fi and WiMAX, eefficient broadband connectivity, wider coverage and improved service quality is desired but limitations exist due to un-coordinated dynamic spectrum management (Sagari, Baysting, Saha, Seskar, Trappe and Raychaudhuri, 2015). In addition, Capretti, Gringuli, Facchi and Patras (2016) enumerated limited roaming capability, inflexible multiple-access and unguaranteed adaptation characteristic of co-existing LTE/Wi-Fi wireless network under scrutiny. A primary responsibility of collecting spectrum usage statistics, negotiating and setting radio parameters based on information exchange with neighbors is required to be made minimal for radio devices within wireless network domain or cloud-based level (Karimi, Seskar and Raychaudhuri, 2018). Various operational techniques of spectrum allocation and sharing triggers events like discovery, cognition, reconfiguration, healing and optimization in multi-radio environment. These multiple radio devices and associated RATs in practice make up a population of entities with exchange of information as events happen. Wireless system components evaluate to achieve connection stability and mobility management (Mauri, Gharfoor, Rawat, Samuel and Perez, 2014). Significant resources demands to cater for effectiveness as resources are optimized help meet user-specified conditions for stabilized connection. A methodology of genetic algorithm to implement a multi-objective function and evaluate radio parameters for fitness is considered. Selection probability of bit error, interference, throughput and power is proportional to their fitness. Genetic algorithm is more efficient and robust because user experiences remain unhindered.

Since management and co-ordination of radio resource parameters is specifically sought to enhance user experience, these operating parameters (bit error, interference, throughput and power) are selectively studied and analyzed to evaluate their fitness within a joint architecture. In this paper, optimizations guarantee steady-state adaptation techniques for more efficiency and effectiveness. Formulation of multi-objective function to jointly evaluate parameters for fitness in this paper is a methodology of contiguous orthogonal frequency division multiplexing (C-OFDM), which is applicable in adaptive environment where co-existence of licensed and unlicensed users are enabled on shared bands (Jinadu, Akinbohun and Owa, 2015) and (Jinadu and Aliu, 2018).

To optimize, parameters with higher fitness are identified as offer for better solutions Motivation for an overall multi-objective function evaluation in shared environment where several objectives are competing require a set of possible obtainable solutions rather than single optimal solution. These solutions are optimal as they are superior to other solutions when objectives are considered equally. Simultaneously minimizing bit error rate and outband (ob) interference while maximizing throughput and transmission power without loss of generality, the multi-objective function evaluates to implement combinatorial optimization for several fitness processes (Reeves, 1997). As investigated in Chen and Wyglinski (2009), a general formulation of separate fitness functions for bit-error, interference, throughput and transmission power showed an inter-dependence of relations.

## 2 Background analysis and reviews

A fundamental characteristic of genetic algorithm (G.A) is their use of population of many parameters. A population of multiple radio devices and associated RATs in practice make up a population of entities, consisting of radio devices within the wireless domain, at radio device, network domain or cloud-based levels, capable of exchanging information as events happen. Recombination of parameters is carried out using genetic crossover and mutation (Vose, 1994). Search and selection of these parameters is guided by the results of evaluating the objective function $f$ for each parameter in the population. Parameters with better solutions are given more opportunity to breed as discussed in Reeve (1994) and Reeves and Rowe (2001).

An optimization framework developed for distributed cognitive radio network in Chen and Wyglinski (2009) stipulated separate fitness function evaluation for radio parameters. For effectiveness, a cross-layer optimization technique of parameter recombination is essential for use in shared bands (3.5GHz, TV White Spaces and part of 5GHz band). Multi-objective functions optimizes selected parameter and as well include sub-carrier implementation as an offer for sustained connectivity and higher data rate transmission proof over extremely hostile channels. The technique offer several benefits of resilient RF interference, spectra efficiency, reduced multi-path distortion among others.

Optimizing radio resource as an offer of maximization and minimization offer improved data rate for ubiquitous computation. With fusion of many technologies, mathematical gaming between service providers stimulates development of fitness function for adaptation and self-healing. Optimization technique as a methodology of reducing multi-path distortion is a good candidate for efficient broadband connectivity and unlimited roaming. For end-to-end communication efficiency where user performance is not compromised, maintenance policy and constraints specified must prevent throughput starvation and also minimize time delays. For the several benefits of resilient RF interferences, spectra efficiency, reduced multi-path distortion among others, self-adaptation and self-healing of RAT usage efficiency depend on operating parameters performance. These are transmission power, bandwidth, carrier frequency and modulation index, providing required intelligence for the system via learning. Wireless radio area network (WRAN) standards stipulate accuracy of PHY layer performance dependence on sensing. Feature extraction detection method, where licensed and unlicensed users share resources are agnostic to MAC-layer techniques (Chowdhury, Kader and Raman,2012). To provide required agility at radio level, systems intelligently implement adaptation and self-healing capabilities via sensing (Falaki, Adewale, Alese and Jinadu, 2018). Sensed information stored in geolocation database help connected RAT entities adjust operating frequency flexibly while transmitting without causing interference to other cooperating entities. The idea evaluates multiple RATs population using formulated multi-objective function. Also, IEEE 802.22 standard enables centralized PHY-MAC layer implementation to exploit vacant TV spectrum bands known as TV White Spaces (Zhao, Tong and Swami, 2005). The standard provides protection for licensed user (LU) through associated spectrum sensing and geolocation database management to enable profitable co-existence between LU and unlicensed user (UU) while equally supporting coexistence with other WRANs (Qualcomm, 2013, 2015). Co-existence, roaming procedures and inter-operation supports user mobility across multi-vendor service system with heterogeneous technologies. Roaming includes updating location information while re-routing incoming user traffic request to accommodate many different forms of selections for continuity efficiency. Allowed inter-operation is also facilitated by the cooperating parallel fitness functions.

## 3 Multi-objective formulation

Our goal here is to significantly improve user experience by performing crossover and mutation at the instance of user specified conditions in shared bands. Added opportunity of next generation communication effectiveness with cellular systems spectrum efficiency and utilization, a multi-objective function is formulated in agreement with Chen and Wyglinski (2009) to evaluate the contiguous orthogonal frequencies and their multiple carriers where each sub-carrier possess its own parameters as environmentally sensed. Sub-carriers components of each carrier frequency on assumption of M interconnected transmitting RAT entities featuring n sub-carriers. Optimization engine of each entity simultaneously configures to optimize selected operating parameters in parallel across all active entities.

Selected parameters modeled for fitness are transmission power $P$, modulation index, $b$, carrier frequency, $f$ and bandwidth $w$. Modulation index evaluate to throughput, Th while allocated bandwidth is subjected to interference. Fitness of each entity i participating intelligently within selected

RAT population is defined as

$$f(\bar{x}) = \sum_{i \in \{Pe,Th,P,Int\}} w_i f_i(\bar{x}) \quad (1)$$

where $w_i$ is weight, $f_i$ the separate fitness function of each RAT entity and the vector of all radio parameters sensed in cognitive environment. With Pe representing probability of error for Th throughput, $P$ is the transmission power and Int represents an out-band interference. Algorithm for determining the intelligence offered by each RAT is expressed in (2). Connecting $M$ cognitive entities where $m = 1, 2, , M$ operates with $N$ carriers, observed quantity as a vector of all radio parameters is determinable over all sensed parameters and associated weights.

$$\bar{x} = \cup_{i=1,\ldots,M}(\cup(\{P_{i,n}, b_{i,n}, f_{i,n}, w_{i,n}\})) \quad (2)$$

Variation in population size and initialization method enable selected entity employ non-contiguous OFDM transmission each time a spectrum hole is detected, placing strict requirements on bit error and throughput measurements. SNR characteristic feature of wireless PHY layers also enable hard constraints on transmission power and throughput measurement. With this assumed characteristics, expression (1) is reconstructed as given in (3).
Maximize

$$f(\bar{x}) = \sum_{i \in \{Pe,Th,P,Int\}} w_i f_i(\bar{x})$$

subject to

$$f(\bar{x}) > \tau, i = Pe, Th \quad (3)$$

where the constraint value $\tau_i$ and $Pe$ are obtainable from symbol error rate (bit-error). When N becomes very large, numerous OFDM carriers and subcarriers account for increased - roaming capability, wireless users and diverse applications. This enhancement further suggests reduced multipath distortion, and evidently reduced transmission latency. Expressed in (4), expected time to transmission equates to number of carriers as transmission entities implement combinatorial optimization, which is summarized and for large number of carriers and sub-carriers within selected RAT population.

$$E(TTR) = N \quad (4)$$

### 3.1 Population adaptation algorithm

To examine interaction of RAT components (population) defined in the multi-objective function expressed in (2), some definitions are made to support user specified conditions (such as application type and duration). The outlined definitions [I VI] is assumed for performing genetic crossover and mutation while a genetic algorithm to generalize performance while accommodating different forms of selection is given in fig.1. The process terminate whenever new population is obtained.

Choose an initial population of RATs;
**while** termination condition not satisfied **do**
**repeat**
**if** crossover condition satisfied then
[select parent RAT;
choose crossover parameters;
perform crossover];
**if** mutation condition satisfied **then**
[choose mutation points;
perform mutation];
evaluate fitness of offspring parameter
**until** sufficient offspring created;
select new RATs;
**endwhile**
Fig. 1 Genetic algorithm template for evaluating parameter

[I]. Let each RAT transmitting entity be assigned a unique identifier from range , where N is the upper bound of population size , and represent a universal set of available channels accessible by each RAT that can potentially be used to connect entities. All entities know , and and are capable of operating on any of the channels in . Each entity is aware of channel availability set . This is the same for every RAT entity.

[II]. Entities and as neighbors (in-band and out-band) represent undirected edge or pair of directed edge in graph. With and in the population size, and being close within other radio range, transmission between these entities is achieved by single hops where $A_iA_j \neq 0$.

[III]. Communication between entities that are not neighbors is achieved by multi-hop. This is a simulation of parallel optimization of the separate fitness functions.

[IV]. Selection probability of any parameter is proportional to its fitness provided the selection is not ranked. Suppose transmission power P is linearly ranked kth in the population, making the algorithm more efficient, as selection probability is expressed in given in (5). $P[k] = \alpha + \beta k \quad (5)$ where and are constants and being a probability distribution function satisfying condition expressed in (6) to enable choice of other parameter freely tuning to selection pressure expressed in (7). $sum_{k=1}^{M}(\alpha\beta k = 1) \quad (6)$

$$\phi = \frac{Prob.[selectingfitnessParameter]}{Prob.[selectingaverageparameter]} \quad (7)$$

[V]. Crossover implementation replaces some parameters of entity $i$ by corresponding parameters of $j$ to generate new population.

[VI]. Optimization become adaptive when objective of determining optimal values of Access Points $APs1, 2, ,$ or that can optimize queuing performance of each unlicensed user (UU) entity in shared band is set to enable crossover or mutation.

# 4 Discussion and Enhancement

Crossover is implemented by replacing some of the parameters in $\mathrm{RAT}_1(|A_1|)$ by the corresponding parameters of other $\mathrm{RAT}_2(|A_2|)$, both of which are in the population. Required proof to evaluate co-existence of $i$ and $j$ as neighbors involve the following test:

**Lemma 4.1.** *With set of possible RAT entities defined in the population, actual transmission occurs only if transmitting entity is present and shared band channel is available within the new set of offspring (RATs) as new population.*

**Lemma 4.2.** *For every triplet $i, j, c$ where $i$ and $j$ are RAT entities and $c$ the transmitting channel, there is a time-slot $t$ such that (i) only $i$ is scheduled to transmit on $c$ during $t$ and (ii) at least one of the receivers at $j$ is scheduled to receive on $c$ during $t$.*

This proof, offers an improvement of Latin square sensing technique implemented in Jinadu, Owa and Akinbohun (2015). Optimized resource usage is established since selected operating parameter available to all RAT entities utilize in parallel while transmitting on that same band (in-band or out-band) as established in Jinadu, Ijawoye and Ijarotimi (2017).

To jointly optimize resources for reliable end-to-end reconfiguration and self-healing (significantly reduced bit-error) techniques, RAT entities in population size are capable of providing: monitoring and discovery, where members within initial population (in-band) as well as new population (in-band and out-band) enables each entity optimize by collecting statistics from different RATs parameters to implement crossover; negotiation, where RAT entities negotiate conditions for status assessment, crossover or mutation with other available entities while selecting most appropriate RAT parameter required by ; control and co-ordination leveraged among linearly ranked population members (initial and new population), entities must be able to control and coordinate reconfiguration of various population parameters; and interaction with other population entities, internally and externally to effect crossover and mutation respectively.

## 4.1 Evaluation of parallel optimization

Within the OFDM transmission, access points consist of independently modulated symbols. A strict relationship between frequency sub-carriers enabled definition $f_n = nf$ and $f = \frac{1}{T_U}$ with $T_U$ being the symbol rate. OFDM power spectrum of all included sub-carrier demonstrated large amplitude variation obtainable from addition of carriers with different frequencies and modulation techniques. Mathematically, this is expressible as given in (7) where $r(t)$ is received signal power for$a_k PU$ or $a_q SU$ taking $N_c$ as number of carriers.

$$r(t) = \sum_{k=0}^{N_c-1} a_k e^{()} \quad (8)$$

Parallel optimization result in maximum peak to average power ratio (PAPR), which is the same as the number of carriers $PAPR_m ax = N_c$. This is also a realization of pooled spectrum discussed in Jondral (2004). Orthogonal carriers along multipath transmission demonstrated flexible bandwidth utilization and associated scalable number of sub-carriers. Optimal values of APs are obtainable with effective bandwidth theory.

### 4.2 Enhancement of crossover and mutation capability

Crossover between same RAT entities $A_1$ and $A_2$ sharing band on C channel with one-point or two-point cross-points easily generates new population to share the allocated band. Also cross-layer (between different RAT entities $A_1$ and $B_1$ or $A_2$ and $B_2$) optimization of RATs entities and the combinatorial engagement in parallel effect mutation as further proof of sharing for scalability. With the discussion presented in Reeves (1994) on neighborhood search and Neighbor Discovery Algorithm (NDA) formulated in Jinadu (2016), the use of divide and conquer (DAC) approach was used to efficiently schedule transmission for in-band or out-band sharing of resources on allocated band. This connotes that on same RAT entity, two associations of sharing instances $DAC(A_1, B_1)$ and $DAC(A_2, B_2)$ enabling 1X or 2X cross-point crossovers between their sub-carriers were allowed. This further implies $DAC(A_1, B_1)||DAC(A_2, B_2)$ to denote algorithm obtained while running the two instances concurrently and $DAC(A_1, B_1)DAC(A_2, B_2)$ to denote algorithm obtained while running the two instances serially. Formulated fitness function support the resultant algorithm $DAC(A_1, B_1)DAC(A_2, B_2)$ to apply to three different blocks of user specified conditions to initiate the crossover: first block consisting of x time-slots where all entities in $A_1$ are scheduled to transmit as all entities in $B_1$ are also scheduled to transmit; second block reverse the roles of $A_1$ and third block consisting of recursively invoked blocks implementing commutative property of
$(DAC(A_1, B_1)||DAC(A_2, B_2))(DAC(A_1, B_2)||DAC(A_2, B_1))$. Therefore, establishing $A_1A_2 = andB_1B_2 = , |A_1| = |A_2|or|B_1| = |B_2|$ is guaranteed to signify optimized association of RATs population entities on shared bands.

# 5 Conclusion

The nature of GA is that parallel processing can be used to advantage in combinatorial optimization discussed in this paper. Selection of parameter is directly proportional to the fitness and selection algorithm enhances minimal trade off between efficiency and effectiveness. Variations in population size or initialization method are not concerns for crossover. Overall multi-objective function fitness is a parallel and combinatorial problem, which maximizes power and throughput for all RAT entities while minimizing bit error and out-band interferences. Performance of parameters Pi, w, f and m (Int) in non-contiguous orthogonal transmission is also unhindered whenever spectrum hole is detected. With this arrangement, adaptation at all layers (crossover or mutation) genetically profit user application more so as joint optimization of all entities are more beneficial to users at application level of the network hierarchy.

With the multi-objective function support by the resultant algorithm $DAC(A_1, B_1)DAC(A_2, B_2)$, the function evaluates genetically to offer efficient spectrum utilization while providing for effective co-ordination. Optimized radio resource operating parameters fitness in shared environment enhances adaptations. With selections being proportional to fitness, optimization reduces multi-path distortion to provide for efficient broadband connectivity, unlimited roaming and profitable sharing. Finally, optimization is adaptive when optimal values of Access Points to optimize queuing performance of LU and UU in shared band is maximized for crossover or mutation technique. New population of RATs techniques are also obtainable with GA techniques as featured network entities (LU and multiple UUs) are enabled to co-exist effectively, sharing parameters to signify scalability.

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