Wireless Pers Commun (2017) 93:287–309
DOI 10.1007/s11277-015-3117-4

A Novel White Space Optimization Scheme Using Memory Enabled Genetic Algorithm in Cognitive Vehicular Communication

Faisal Riaz[1] · Imran Shafi[2] · Sohail Jabbar[3] · Shehzad Khalid[4] · Seungmin Rho[5]

Published online: 12 November 2015

Abstract A dedicated single short range communication link is not efficient for an inter-vehicular communication system and results into degraded performance. To address the problem, a cognitive radio site is proposed as an intelligent vehicular device to implement an inter-vehicular communication network using multiple radio access technologies. Further, the whitespace optimization at vehicular speed is achieved by the memory enabled genetic algorithm. The algorithm makes use of four cognitive radio decision variables as genes including frequency, power, data rate and modulation scheme in the chromosome structure. The performance of the proposed approach is validated against the classical genetic algorithm and particle swarm optimization algorithm. In this research, a statistical evaluation is also presented to confirm the potential of cognitive radio paradigm employing multiple radio access technologies as an option to fulfill the increasing bandwidth demand

✉ Seungmin Rho
korea.smrho@gmail.com

Faisal Riaz
fazi_ajku@yahoo.com

Imran Shafi
imran.shafi@abasyn.edu.pk

Sohail Jabbar
sjabbar.research@gmail.com

Shehzad Khalid
shehzad_khalid@hotmail.com

1 Department of Computing and Technology, Iqra University, Islamabad, Pakistan

2 Department of Computing and Technology, Abasyn University Islamabad Campus, Peshawar, Pakistan

3 Department of Computer Science, COMSATS Institute of Information Technology, Sahiwal, Pakistan

4 Bahria University Islamabad, Islamabad 44000, Pakistan

5 Department of Multimedia, Sungkyul University, Anyang, Korea

of an inter-vehicular communication system. Experimental results demonstrate the effectiveness of the approach by ensuring efficient bandwidth utilization and fulfilling varying nature of users' quality of service requirements in real time.

Keywords Cognitive radio · Multi-RAT · Memory enabled genetic algorithm · Vehicular cyber physical system (VCPS) · White space optimization

1 Introduction

It has been stated by the World Health Organization that about 1.2 million road commuters expire in road catastrophes yearly, and another 50 million get wounded [1]. Also, the young population aged 10–24 years have high death rate due to the road accidents [2]. The death rate due to road accidents is higher in under developed countries as compared to the developed ones [3]. The Pakistan Bureau of Statistics reports 4280 annual deaths in Pakistan in the year 2014 and the rate of accidents is increasing every year [4].

According to Foss et al. [5], one of the main causes of these accidents is the driver. According to Rumschlag et al. [6], drivers perform texting during driving which leads to road accidents. Drivers pay attention towards bill boards on roads which cause cognitive distraction and it leads to the road accidents [7]. According to Lansdown et al. [8], mobile phone conversation diverts the attention of driver and it leads to the severe road accidents.

To address the issue, artificial intelligence has been embedded in the on-board units of modern vehicles, which assist human drivers to avoid the road accidents [9]. This embedded intelligence and hardware in vehicular setup is known as vehicular cyber physical system (VCPS). Whenever, the vehicle faces an alarming situation, the VCPS alerts the human driver by generating warnings to increases his/her attention level. Currently VCPS are available in different shapes like adaptive cruise control systems, lane departure warning systems, early collision avoidance systems and autonomous vehicles (AVs) [10].

To sense the situation beyond the human driver perception, inter-vehicular communication system (IVC) is playing an important role by helping vehicles to exchange their location and speed [11]. For an IVC, many licensed and unlicensed radio access technologies (RATs) like CDMA, Wi-Max, GSM/GPRS, and Wi-Fi IEEE 802.11 g/n/p are in use [12]. However, the existing IVC for accident avoidance makes use of a single RAT. Such a system's performance may get adversely affected in areas where there is no or little coverage of the used radio technology especially in hilly areas and over-burdened radio access networks (RANs). In circumstances when one network is not accessible, a vehicle must be intelligent enough to shift to a different radio access technology in order to continue using communication services. It is reported by various regulatory agencies around the world that 35–70 % spectrum space is wasted due to the lack of licensed users in various technologies [13]. The cognitive radio approach has lately resolved the issue of bandwidth scarcity using its opportunistic spectrum access method [14, 15] with main features being spectrum sensing, spectrum management, spectrum handover, and spectrum sharing [16].

Cognitive framework is only practicable if the spectrum hole is suitably detected and timely assigned to the IVC. This can be effectively performed by using evolutionary computing techniques. Genetic algorithm (GA) has been vastly used to find out the best fit for different types of optimization problems like white space optimization [17]. The technique is used for optimal communication between autonomous vehicles by optimizing the RF parameters of cognitive radio network. For this purpose a Fitness Measure is derived along the customized chromosome structure consisting of RF genes [18]. Another approach makes use of a cognitive radio spectrum management scheme using GA to optimize frequency, bit error rate, power, and modulation scheme [19]. GA has been claimed as the best possible optimization technique by utilizing frequency, power, modulation scheme and data rate as chromosome structure for the spectrum optimization in cognitive radio networks [20]. To enhance the cognitive radio system performance, GA is used to minimize the partial operating parameters like bit error rate, out- of-band interference, and throughput of stationary wireless devices through multi-objective fitness function [21]. However, all these researchers have reported simple GA not responding well in real time vehicular networks. Decision time to select and shift to a spectrum hole in an IVC is critical due to the rapidly changing environment in an IVC network as vehicles are moving at speeds in the range of 60–130 km/h. Reportedly, accident can be prevented if drivers knew about the accident 3 s earlier before the accidents [22].

Keeping the cognitive radio advantages in mind, an intelligent multi radio access technologies (Multi-RAT) cognitive radio framework with white space optimization using memory enabled genetic algorithm (MEGA) is proposed to improve the efficiency and reliability of existing IVC systems. Conventional GA is modified by introducing memory concept which expects to improve the spectrum decision time. The proposed framework introduces four modules as part of a cognitive radio site (CR-Site) that comprises of a scanner, sensor, optimizer, and a shifter module. The scanner module performs scanning of the Multi-RAT to include GSM/GPRS, CDMA, WiMAX, TV band, and unlicensed band IEEE 802.11 g/n. On detection, the sensor module finds the white spaces in these technologies by using dual radio and cooperative sensing. The optimizer module optimizes the white spaces by employing the MEGA according to the user's quality of service (QoS) requirements.

The rest of the paper is organized in four sections. Next Section presents the limitations of existing methods used for IVC with load analysis. The proposed method is given in Sect. 3. Section 4 provides experimental results and discussion about the white space optimization using GA, MEGA and particle swarm optimization (PSO). Section 5 concludes the paper.

2 Limitations of Existing Methods and Load Analysis

In this section, the limitations of existing solutions including IEEE 801.11p and Cognitive radio based VCPS are discussed (Tables 1, 2).

2.1 IEEE 802.11p for Vehicular Communication

The research in vehicular communication has significantly improved after seven 10 MHz channels are assigned in 5.9 GHz spectrum in 1999 [23]. This was followed by the amendments to modify the medium access control (MAC) protocol for multi-channel operations as IEEE 802.11p [24] and IEEE 1609 [25]. However, these dedicated resources are unable to solve the problem of bandwidth allocation due to increasing number of vehicular users competing for the same channel while in the same area [26]. The simulation results on QoS requirements reported in [27] show that the control channels may contribute to large data conflicts. It has also been argued that 10 MHz channel may not be sufficient for use in safety

Table 1 RF radio/antenna and environment parameters

Radio/antenna parameters	Environmental parameters
Frequency of operation	Interference level
Transmission data rate	Multi-path fading
Modulation type	Tracking loss
Transmitted Power	Propagation loss
Coding scheme	Received power levels
Eb/No, BERn	Link margin

Table 2 QoS parameters

Parameters	Frequency (GHz)	Power (dBm)	Data rate (Kb)	Modulation
Values	0–2	−30 to +30	100–700	GMSK, OFDM, spread spectrum

applications. These facts motivate the use of cognitive technology in vehicular communication because it allows opportunistic selection of spectra. The spectrum assigned to wireless access in vehicular environments has also been found insufficient to ensure reliability of data exchange [28]. It has been further confirmed that IEEE 802.11p standard for vehicular communication cannot suffice for the spectrum requirements [29].

The message delivery delay in vehicular networks should be less than 200 ms. A smaller delay in delivery gives more time to the driver to react to the conveyed information [30]. However, it has been shown that the actual delay in delivering a message may exceed 1000 ms [31]. The main reason is the data contention in the control channels. Some vehicular safety applications like adaptive cruise control system and traffic monitoring systems have been implemented and tested. In order to provide better support to these applications, it is required to have a strict threshold on throughput and delay. It has been concluded that IEEE 802.11p reduces data rate in dense highly loaded conditions where packet loss is also found to increase significantly [32]. IEEE 802.11p uses CSMA/CA protocol to address the multiple access problems while many nodes attempt to share the channel. It is well known that IEEE 802.11p suffers from the hidden node problem, which finally results in high communication delays [33]. Such delays are intolerable in vehicular communication. Bilstrup et al. [34] examine vehicular communication and conclude that IEEE 802.11p is not suitable for periodic delivery of information. CSMA has also been found ineffective when used in vehicular setup [35].

2.2 Channel Access in VCPS Environments

Di Felice et al. [36] proposed a cooperative sensing and spectrum allocation scheme to share spectrum of TV channels among vehicles on their path. However, this approach makes use of only a Single-RAT i.e. TV channels, as a potential candidate for cognitive radio-based vehicular communication. A feasibility study of frequency modulation (FM) based vehicular communication system using universal software radio peripheral and GNU radio has been investigated in [37]. This proposition relies on a Single-RAT, which overburdens the band by the regular FM users and vehicles within the same area. Some other approaches propose cognitive radio as a solution for vehicular ad-hoc network (VANET) [38–40].

There are few IVC systems based on fixed RAT IVC system like CDMA but it does not work on blind curves and can cause accidents [41]. Broadband wireless access for users on the road and IVC system based on Wi-Fi is also under consideration. However, the lack of coverage area by this technology is a primary hurdle in its deployment [42].

2.3 Load Analysis of IVC Systems

To prove the validity and benefits of proposed idea, load analysis of different single RAT based VCPS have been performed. Establishing an IVC system based on a Single-RAT can degrade the performance of existing service subscribers as well as not capable of supporting extra burden of vehicles. A field survey is conducted to support this hypothesis. A Pakistani city Mirpur was chosen as the test field, and a survey was carried out to find out total number of registered vehicles in the city to compute the burden to be handled by RANs. A survey was carried out to find out total number of licensed users in the city served in GSM, CDMA, WiMAX, TV, and FM broadcast bands. The city was divided into 20 sectors for this purpose. Additionally, the information about total sites/base-stations operated by various international/national service providers was also gathered. The collected facts/figures regarding number of vehicles, service providers, and subscribers are given in Table 3. The facts and figures in the Table are used to compute:

1. Existing burden of voice/data traffic on BTSs of different service providers.
2. Extra user load of single BTS in case of establishing single GSM/CDMA operator based IVC system.
3. Extra user load to be handled by a BTS in case of establishing multiple GSM operators based IVC system.

The analysis and comparison of different IVC systems are given in Table 4. For load analysis of Single-GSM service provider (SP) based IVC system, we have chosen SP3 (An international GSM service provider company in Pakistan). SP3 has total 12 GSM/GPRS sites in Mirpur as shown in Table 8. Each site is currently serving 788 people, and it can be 1575 users per site after deploying an IVC system. This is almost doubled in existing serving capacity of each SP3 site. Load analysis of Multi-GSM service providers based IVC system (SP2, SP4, and SP5) is found better than single-RAT based IVC system. CDMA based IVC system (SP1A) shows heavily overburdened sites after deploying vehicular network. However, the Multi- RAT based IVC system (GSM/GPRS, CDMA, and Wi-Fi) performs better by shifting the vehicles on existing communication network in terms of least loaded

Table 3 Total vehicles, service providers and subscribers in Mirpur

RATs	Service providers	Users	Total	BTS/boosters	Registered vehicles
GSM	SP1	29,000	139,672	6	28,337
	SP2	31,595		8	
	SP3	37,365		12	
	SP4	9500		7	
	SP5	27,487		6	
CDMA	SP1A	4725	4725	4	
FM	FM-90	110,000	187,500	1	
	FM-93	77,500		1	
TV	PTV	8000	8000	1	

Table 4 Comparison of different IVC system in terms of traffic load

Available IVC systems in Mirpur city	Existing burden (Per Site) (without IVC system)	Total burden (per site) (with IVC system)	Vehicles (per site)
Single-GSM service provider (SP3) based IVC system	788	1575	787
Multi-GSM (SP2, SP4, and SP5) service provider based IVC system	767	1009	242
CDMA based IVC system	315	2204	1889
Multi-RAT (GSM + CDMA + Wi-Fi) Based IVC system	682	897	215

networks. The performance of Multi-RAT based IVC system is expected to improve further if white space optimization can be performed by some evolutionary approach.

3 The Proposed Method

The block diagram of the proposed method is shown in Fig. 1. The result of the in-field survey for the load analysis of Single-GSM service provider (SP3), Multi-GSM service providers (SP2, SP4, and SP5), and Multi-RAT (GSM + CDMA + Wi-Fi) based IVC system confirms the superiority of Multi-RAT (GSM + CDMA + Wi-Fi) based IVC system. Subsequently, a CR-Site has been proposed for real-time implementation of Multi-RAT (GSM + CDMA + Wi-Fi) based IVC system. The memory enabled genetic algorithm is used in the optimizer module of CR-Site for white space optimization in real time IVC system environment. Comparative analysis of GA, MEGA and PSO has been performed in terms of CPU convergence time.

We have considered cognitive radio enabled cellular communication networks along with Wi-Fi as a suitable solution. The reasons for choosing cellular communication infrastructure for vehicular networks are their better coverage in the inner-city intersection scenario (specifically T-Junctions), the high position of the cellular base stations, and a lower frequency property as compared to the ad-hoc networks [43]. The notion of cognitive radio has already been examined to resolve the exponential data traffic escalation in cellular networks [44, 45]. From a field survey conducted in the dense population area of a Pakistani city Mirpur (AJK), the existing RANs are found overburdened. Deploying a vehicular network on any one of these RATs can degrade the performance of the particular RAN. Further, the cognitive radio based IVC systems reported in [36–39] relying on a Single-RAT are not efficient. Accordingly, employing Multi-RATs in cognitive environment avoids single RAN to bear the full vehicular communication traffic load. Another advantage of using Multi-RATs is availability of multiple types of white spaces in different bands that can fulfill varying QOS demands. For example, to initiate video conferencing white spaces in WIMAX or TV band are more suitable but for short range data exchange, Wi-Fi suffices.

The proposed cognitive site (architecture shown in Fig. 2) consists of four main modules, those are:

- Scanner: scans the available RATs within the range of vehicle movement.
- Sensor: senses the white spaces if opportunistic access mode is set else simply shift on another available spectrum band.

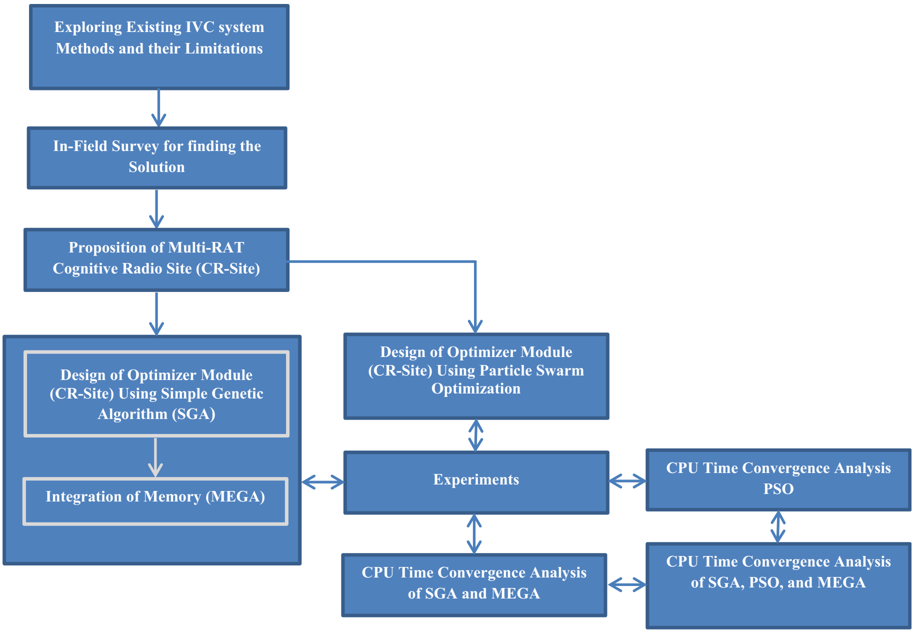

Fig. 1 The method

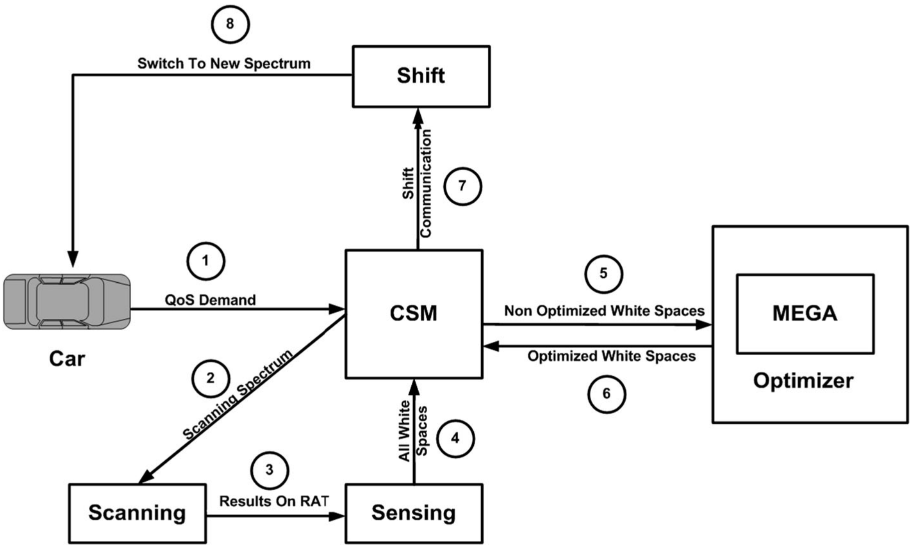

Fig. 2 Internal architecture of CR-site

- Optimizer: finds the optimized white spaces in order of priority using efficient spectrum decision MEGA module according to the vehicle QOS request and shifting of available white space.
- Analyser: Continuously analyses performance of allotted white-space to perform efficient transfer the IVC system on next available spectrum hole.

A cognitive system monitor (CSM), acting as brain of CR-Site, coordinates the four modules. The steps and pseudo code of algorithm depicting the functioning of CR-Site and theoretical description is presented in the next sub-section.

3.1 CR-Site Functioning Algorithm

```
Start
 DO
  1: Vehcle Genrates QoS_Request → CSM(QoS Parameters)
  2: CSM → Initiate Scanning_Multi_RATs()
3a: IF Opportunistic Spectrum Access < −True
        CSM < −Multi − RAT_Whitespaces_Pool
        CSM → Initate MEGA (Multi − RAT_Whitespaces_Pool )
              MEGA
                → Optimized (Multi − RAT_Whitespaces_Required QoS)
                + Maintain Memory Table
              IF (Whitespaces_Requested QoS = First Time)
              Vehicle → CSM ( MEGA(Whitespaces_Required QoS))
               Else
                  Vehicle < −CSM (MEGA (Memory Table ) )
               ENDIF
               IF (Channel_loss( ))THEN
               Call_Channel_Shifting Module ()
    Else
  3b: Vehicle < −CSM (Suitable RATs_SIR+Cost )
       EndIF
ENDDO
END
```

3.2 Theoretical Description of CR-Site Functioning Algorithm

The step by step description of CR-Site algorithm is given as under:

1. Vehicle generates call request for channel allocation to the cognitive system monitor, for this purpose vehicle has to pass QOS demand to the CSM as well.

The RF parameters have been divided into radio/antenna and environmental parameters as shown in Table 1. Radio/antenna parameters exhibit such values that have a direct relation to the functionality of radio, because environmental parameters have a relation with the network layout and its geographic topology [46]. For the sake of simplicity, only four radio/antenna parameters like frequency, power, modulation type and transmission data has been used and are shown in Table 2. The chromosome structure of GA, MEGA and PSO uses these QoS parameters as genes.

2. CSM invokes scanning module to scan all the available RATs using Multi-RAT scanning enabled hardware.
3. After the scanning module, CR-Site uses following two options:

- In the first option, if opportunistic spectrum access mode is set, then available channels information is passed to the sensing module. To avoid the problem of hidden terminals, as the nature of our problem, cooperative sensing has been suggested [47]. In sensing module matched filtering, energy detection, and cyclostationary techniques are employed to detect the primary user (PU) [48]. In the result, white spaces will be passed to the CSM, which maintains the pool of available white spaces. After this step, CSM employs MEGA module to find the optimized white spaces efficiently. CSM then employs MEGA to find optimized white space from the pool of available white spaces according to the QOS parameters received from the vehicle and assigns to the vehicle. The shifter module is invoked to switch the vehicle to the newly assigned white space. After the successful white space allocation, CSM continuously analyses that the allotted white space is good enough to fulfil the needs of the user. Meanwhile sensing module will continuously sense the channels, and keep CSM updated about PU activation status. Dual radio sensing architecture is employed to carry out this task efficiently. One radio chain is dedicated for data transmission and reception while the other chain is dedicated to spectrum monitoring [47, 49]. If CSM finds PU status active on assigned white space, then new white space will be allocated to the vehicle, after performing optimized white space and shifting process.
- In the second option, a suitable RAT will be selected among available RATs on the basis of signal to interference ratio (SIR) and cost of service. The most suitable channel is passed to the CSM, which allocates it to the vehicle. CSM continuously monitors the channel condition and if the channel degrades its performance, new channel allocation process is initiated by the CSM.

4 Discussion on Experimental Results

4.1 White Space optimization

Let RAT_iWS_{ijk} here $1 \leq i \leq N, 1 \leq j \leq N, 1 \leq k \leq N$ like RAT_1WS_{111} representing $(RAT_1 = GSM, RAT_2 = CDMA, RAT_3 = LTE, RAT_4 = Wi - Fi, RAT_5 = WiMax)$ whereas in WS_{ijk}, i represents service provider [(where i = 1 represents Ufone, for i = 2 Telenor, and i = 3or Mobilink, the three cellular service providers in Pakistan), (j represents tower number of service provider and k represents the number of white spaces)]. RAT is GSM, Service provider is Ufone, BTS is 1, and white space counter is 1. In Table 5, a pool of white spaces maintained by CR-Site is shown.

When a single unit (SU) depicting a vehicle has to transmit data, a white space is optimized according to the QoS parameters of the application from the available white spaces within the white space pool. The complete scenario of a multi-radio access technologies spectrum sensing and white space pooling has been presented in Fig. 3. SU', SU'' and SU''' are showing the different spatial positions of the same vehicle. The vehicle is equipped with a proper software defined radio and CR-Site as shown in Fig. 3. At each spatial location vehicle sense and generate a multi-RAT whitespaces pool. Table 5 is showing a sample multi-RAT whitespaces pool.

4.2 Modified GA to Find Optimized White Spaces

The Genetic Algorithm is beneficial in cognitive radio and has been applied to solve different issues related to the cognitive radio networks [50–52]. However, GA is not suitable for fast computations specifically in time-critical application like IVC systems. GA optimization requires numerous iterations and computations to provide an optimal solution and is time-consuming. Accordingly, GA is not preferred for real-time applications.

We propose integration of memory in GA (MEGA) to save time and continuously update optimized white spaces against the current QoS. Once, the vehicle initiates white space request using QoS parameters for the first time, MEGA works like simple GA and its memory table is initialized to null. On process completion, three white spaces in order of priority are stored in the memory table. Though, the first whitespace is assigned to the vehicle but the second and third options are also available in the memory table of MEGA. Later, whenever a vehicle request for the same QoS parameters, the top value from memory table is assigned to it without process initiation thus saving time, computation and memory. However, the GA continuously keep updating the memory table with the white spaces after certain time.

The suggested chromosome structure comprises of four cognitive radio decision variables as genes including the frequency, power, data rate and modulation scheme. The structure of chromosome with sequence and associated genes limits has been shown in Table 6. The first gene in chromosome structure is frequency and can be denoted as F with

Table 5 White space pool maintained by multi-homing enabled CR-site

RAT_iWS_{ijk}	RAT_1WS_{111}	RAT_1WS_{322}	…	RAT_1WS_{nnn}
RAT_iWS_{ijk}	RAT_2WS_{111}	RAT_2WS_{122}	…	RAT_1WS_{nnn}
RAT_iWS_{ijk}	RAT_3WS_{111}	RAT_3WS_{222}	…	RAT_1WS_{nnn}
RAT_iWS_{ijk}	RAT_4WS_{111}	RAT_4WS_{122}	…	RAT_1WS_{nnn}
RAT_iWS_{ijk}	RAT_5WS_{111}	RAT_5WS_{222}	…	RAT_1WS_{nnn}

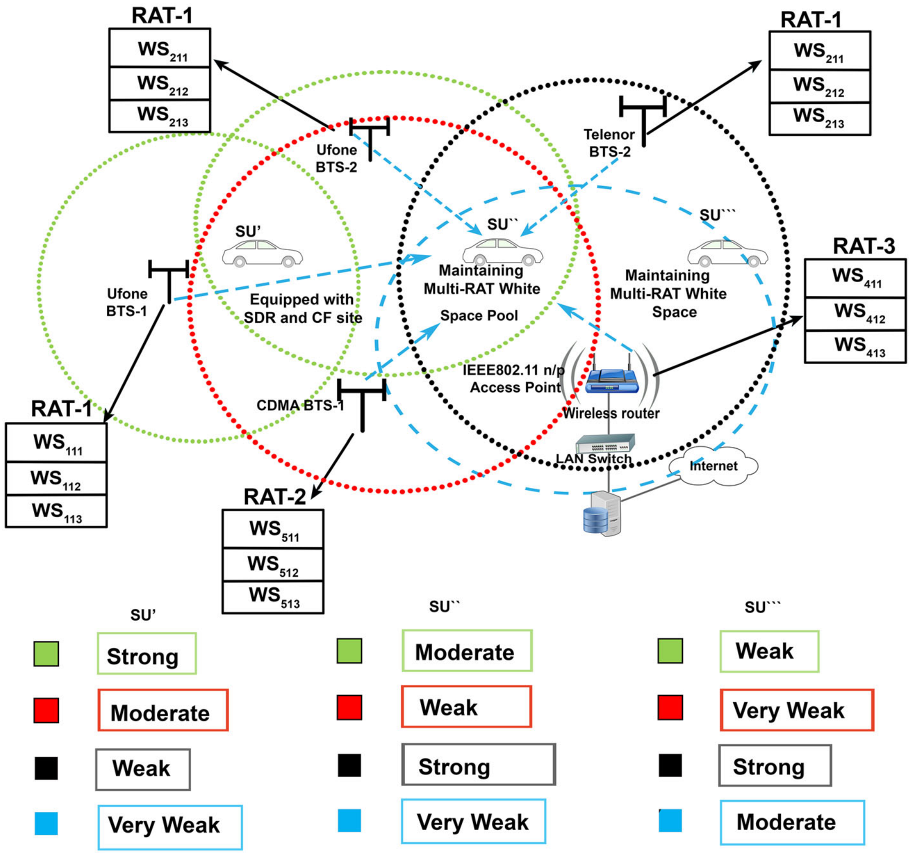

Fig. 3 Multi-RAT spectrum sensing and white space pooling

Table 6 Chromosome structure

Sequence	Chromosome gene	Limits (decimal numbers)	Bits for binary representation
1	Frequency (F) in Hertz	0–999	10
2	Power (P) in watt	0–60	6
3	Data Rate in bits/second	0–7	3
4	Modulation Scheme (M)	0–3	2

limits from 0 to 999. This gene requires total 10 bits for binary representation. The second one is power and can be denoted as P with limits from 0 to 60. This gene requires total 6 bits for binary representation. The gene data rate has been placed at number three in the structure of chromosome. The limits for data rate are from 0 to 7. This gene requires total 3 bits for binary representation. The fourth and last gene in the chromosome structure is modulation scheme having limits from 0 to 3 and denoted as M. This gene requires total 2 bits for binary representation.

In total, there are 21 bits representing the chromosome to be used for mutation. The values of control parameters used in the experiments are population size = 100, crossover rate = 4 %, Generation = 450, and mutation rate 0.05 %. The very first population in the genetic algorithm is generated randomly. The approach uses substitution type of mutation and one-point crossover in MEGA.

The fitness function helps in decision-making. The initial population of chromosomes will undergo the fitness function and can generate unpredictable results because it is generated randomly. Some results are found to be very close to the optimal solution and some are not. The next generation totally depends on the fitness function of the algorithm and is not possible without the fitness function. This fitness function is just like a test where every chromosome in the population has to undergo the fitness function [53]. For simplicity, we consider fitness function by assigning equal weights to all four genes in the chromosome. However this can vary depending on the application or request by the user. The user can increase the weight of power and compromise on other parameters.

The selection in genetic algorithm includes selecting the best offspring or chromosome from number of chromosomes [54]. The fitness function of chromosome provides the basis for selection. The techniques like Roulette Wheel selection, tournament, rank-based, and deterministic methods can be used [55]. The Roulette wheel selection method is also called "Fitness proportionate selection" method. This method is used for recombination of the better solutions in the next generation. It works by using associated probability to each chromosome using following equation.

$$\text{Probaility}(i) = f(i) / \sum_{j=1}^{N} f(i)$$

P(i) in the above equation refers to the probability associated with each chromosome in the population, *f(i)* is representing the fitness of the chromosome where *i* is index number and N is representing the total chromosomes in population. According to Roulette Wheel selection method the chromosomes having higher probabilities will survive for the next generation, and there will be a restriction on the chromosome with lower probability to transfer in the next generation. After selecting the chromosomes with higher fitness the next step in GA is to perform the operation such as crossover and mutation.

The fitness of the first gene in the chromosome structure is calculated by taking difference between the value of frequency gene in the chromosome and the frequency band that is requested by the SU or application. The absolute difference is calculated as:

$$\text{Difference(D)} = |\text{Requested frequency band} - \text{frequency band in chromosome}|$$

The above equation will give us the difference between QoS frequency and frequency band in chromosome in the form of positive decimal number. After getting this difference, we have to specify a variable "P" between the specified limits on the frequency (i.e. 0–999). This can be any number within limits, e.g. we consider 300. We have two different equations for calculating the fitness of frequency band on the basis of variable "P". If the calculated difference is less than P then we have following equation.

$$\text{Fitness(F)} = \text{x} * (|(\text{D})|/\text{P})$$

where the "x" represents the specified weight of frequency band in chromosome and "D" is the difference between value of frequency gene in the chromosome and the frequency band which is requested by the SU or application. Here, "x" represents 25 because 25 %

weight has been given to each parameter in chromosome. If the calculated difference is greater than P, then following equation is used.

$$\mathrm{Fitness(F)} = \mathrm{x}$$

The fitness calculation of power gene in the chromosome is on similar lines. The difference between requested power by the user and the power in the chromosome that is under consideration is calculated using following equation:

$$\mathrm{Difference(D)} = |\text{power in QoS} - \text{power in chromosome under consideration}|.$$

Here, the power parameter "Q" should be within the specified limits for parameter Power (0–60). If the calculated difference between requested Power band and power band in chromosome using equation is less than specified "Q" than the fitness of the power gene is calculated using the following equation.

$$\mathrm{Fitness(P)} = \mathrm{x} * (|(\mathrm{D})|/\mathrm{Q}).$$

The "x" is the weight of power gene in weight of overall chromosome and is fixed at 25. Now if the difference is greater than specified value of "Q", then following equation is used:

$$\mathrm{Fitness(P)} = \mathrm{x}.$$

The data rate gene has been placed at number three position in the structure of chromosome. The fitness function for this gene is calculated on similar lines as done for the frequency and Power fitness functions. The fitness function of Data Rate starts with the calculation of the difference between the requested data rate by the user or application and the BER in the chromosome under consideration, given as under:

$$\mathrm{Difference(D)} = |\text{Data Rate in QoS} - \text{Data Rate in chromosome under consideration}|.$$

The variable "R" is considered which can assume values in the range of (0–7). If the calculated difference between the Data Rate in QoS requested by the user or application and the data rate in the chromosome under consideration is less than specified value of "R" then following equation is used to calculate fitness.

$$\mathrm{Fitness(P)} = \mathrm{x} * (|(\mathrm{D})|/\mathrm{R})$$

where the variable "x" represents the contributed weight of data rate gene in overall weight of chromosome which is fixed at 25 and D represents the difference. In the second case, if the calculated difference is greater than the value specified by variable "R" then following equation is used.

$$\mathrm{Fitness(P)} = \mathrm{x}.$$

The fourth gene in the structure of chromosome is modulation scheme. The process of calculating the fitness of this gene is different from the methods used in first three genes. The difference between the modulation scheme requested by the user or application and the modulation scheme in the chromosome under consideration is found using following equation.

$$\text{Difference(D)} = |\text{Modulation in QoS} - \text{Modulation in chromosome under consideration}|.$$

If the calculated difference is equal to 0, that is mean that the modulation scheme has exactly matched the requested modulation scheme, and fitness will set to 0 as well. On the other hand, if the difference is not equal to 0 than it means that modulation scheme has 100 % non-matching characteristic. In such case, the fitness will set to 25 which means it is far away from the optimal solution.

4.2.1 Integration of Memory in GA

The flow diagram of proposed spectrum decision scheme using MEGA is depicted at Fig. 4. It can be seen that a memory module has been introduced to keep track of optimal solutions from GA in a memory table. An SU (Vehicle) requests same QoS parameters only when the white space become unavailable due to PU activation or bad signal strength due to mobility. The proposed technique, by integrating memory in GA, saves time and updates optimal white spaces against the QoS requirements. It does not repeat steps for the same QoS parameters to find the white space once found as the same are already stored against the parameters and need to be simply retrieved for similar parameters requested by SU. However, the proposed method keeps updating the white spaces after specific time intervals and stores them in the memory. A new white space is assigned to the SU from the dynamic table maintained in the memory module of MEGA whenever the spectrum handover is requested due to the availability of PU or bad signal strength.

4.3 Experimental Testing

A simulator is designed in C#.net platform to verify the idea of proposed MEGA algorithm. To maintain the consistency of testing, various test cases have been designed for GA, MEGA, and PSO and are presented in Table 7. Each test case consists of four QoS parameters with different values.

It is important to mention that each test is repeatedly passed to the GA and MEGA simulator for improved results. Multiple tests are conducted for GA and MEGA and their means along with standard deviation values are also computed. The experimental results have been reported in Table 8. For the test case 1 (Table 7), the CPU convergence time using genetic algorithm without memory table is 599.30 ms with standard deviation of ±7.617, whereas MEGA takes 0.556 ms with deviation of ±0.107. Similarly, for test case 5, genetic algorithm takes 581.10 ms and MEGA takes 0.461 ms with standard deviation of ±11.090 and ±0.047 respectively. From the comparative analysis of all test cases, it is concluded that the proposed approach using MEGA has significantly improved performance in terms of CPU convergence time over genetic algorithm. Further experiments verify that the proposed approach using MEGA takes 0.523 ms for white space optimization as compared to genetic algorithm taking 590.83 ms for the same task on average.

4.4 Particle Swarm Optimization to Find Optimal Spectrum Holes

Particle Swarm Optimization (PSO), developed by Eberhart and Kennedy [56], is based on collective behavior of particles flying through search space with each particle representing a potential solution. Evolutionary and swarm algorithms such as GA/PSO are being used

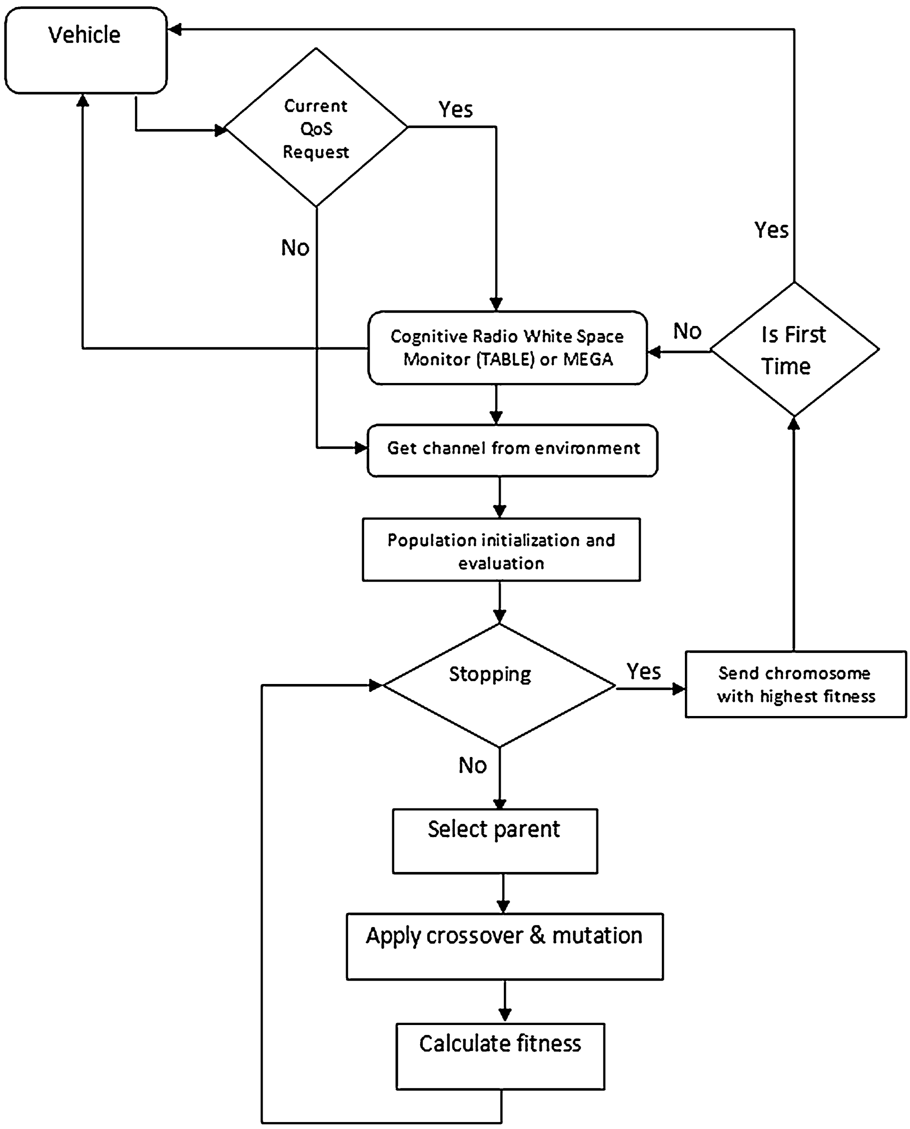

Fig. 4 Efficient white space allocation to a vehicle using MEGA

for efficient resource allocation in cognitive radio networks [57]. QoS parameters such as BER and Power are optimized using adaptive discrete particle swarm optimization (ADPSO) [58]. The results proved that the convergence time of ADPSO is less as compared to other adaptive techniques. PSO is also applied to adjust the parameters for dynamic resource allocation [59]. PSO algorithm shares common characteristics with genetic algorithm and other evolutionary techniques [60]. Both the algorithms are initialized with the randomly generated population. Population consists of number of potential solutions that is evolved in updating generations, and both utilize a fitness value

Table 7 Test cases consists of different QoS parameters for GA, MEGA and PSO

Test case no	Frequency	Power	Data rate	Modulation scheme
1	10	60	4	2
2	999	30	7	3
3	498	10	1	1
4	100	40	5	2
5	200	50	4	0
6	350	100	0	1
7	500	20	6	3
8	300	23	0	0
9	85	25	1	1
10	350	1	5	0

Table 8 GA and MEGA convergence in terms of CPU time using icore3 processor with 4 Gb RAM

Sr. No.	White space optimization with SGA (ms)	White space optimization with MEGA (ms)
1	599.30 ± 7.617	0.556 ± 0.107
2	593.10 ± 9.848	0.598 ± 0.160
3	591.30 ± 8.525	0.482 ± 0.047
4	589.70 ± 12.841	0.512 ± 0.120
5	581.10 ± 11.090	0.461 ± 0.047
6	583.50 ± 3.923	0.594 ± 0.254
7	587.00 ± 7.394	0.542 ± 0.197
8	586.20 ± 9.716	0.514 ± 0.078
9	586.30 ± 5.250	0.517 ± 0.148
10	581.10 ± 11.090	0.462 ± 0.040

to evaluate population. The main difference is PSO do not use genetic operators such as crossover and mutation like GA so PSO population do not die out in any generation.

In order to get a better performance comparison, we have used PSO to find the optimal solution for finding white spaces in parallel to the proposed approach using MEGA. The structure of the particle is kept same like used in GA. The results are presented in Table 7 for PSO and genetic algorithm which indicate superiority of PSO over GA.

To update the position of the particles, following equation is used:

$$x_{k+1}^{i} = x_{k}^{i} + \upsilon_{k+1}^{i}$$

where x_k^i is the current position of the particle, i and x_{k+1}^i are the updated position. The velocity υ_{k+1}^i is updated by using the following equation:

$$\upsilon_{k+1}^{i} = w_k \upsilon_k^i + c_1 r_1 \left(p_k^i - x_k^i\right) + c_2 r_2 \left(p_k^g - x_k^i\right).$$

We have chosen the values for $c_1 = 2$, $c_2 = 1$ $r_1 = 0.1$, $r_2 = 0.1$, $w_k = 1$ and $\upsilon_k^i = 1$. Values for all these parameters are taken after performing tests by taking different values

Table 9 Test class I

c1	c2	r1	r2	wk	υik
2	2	0.7	0.2	1	1
1	1	0.6	0.1	1	1
2	1	0.1	0.1	1	1
1	1	0.2	0.2	1	1
2	2	0.3	0.3	1	1

Table 10 Test class II

c1	c2	r1	r2	wk	υik
2	2	0.7	0.2	1	2
1	1	0.6	0.1	1	2
2	1	0.1	0.1	1	2
1	1	0.2	0.2	1	2
2	2	0.3	0.3	1	2

of each parameter. Two different test classes with five test cases have been designed to check the efficiency of PSO for the optimization of cognitive radio white spaces. Test class I and test class II parameters are shown in Tables 9 and 10 respectively. Initial velocity of particles is fixed as 1 in test class I and is set at 2 in test class II. These test case parameters are used to compute the most efficient convergence time of PSO algorithm for white space optimization.

Comparison of the two test classes is shown in Fig. 5 which indicate the convergence time of test class I being less than test class II. Multiple tests are run for each class with different values of particle's dimensions and the mean values are retained for performance comparison. The average time consumed by the PSO algorithm is 36.44 ms and is faster than GA which takes 590.83 ms to carry out the optimization task.

Table 11 presents the comparative analysis for GA, MEGA, and PSO in terms of CPU convergence time. The CPU convergence time for genetic algorithm is 599.30 ms with

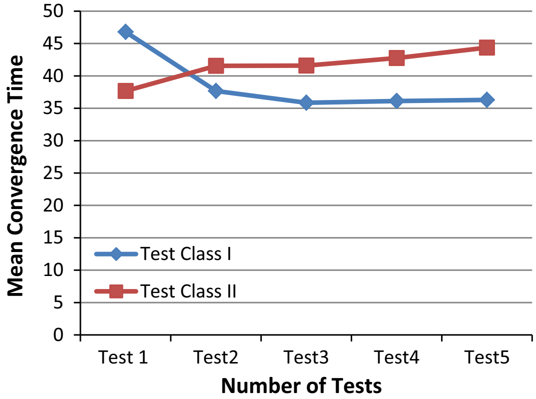

Fig. 5 Comparison of test class I and test class II

Table 11 Experiment results using core i3 processor and 4 Gb RAM

Sr. No.	White space optimization with GA (ms)	White space optimization with MEGA (ms)	White space optimization with PSO (ms)
1	599.30 ± 7.617	0.556 ± 0.107	35.900 ± 2.234
2	593.10 ± 9.848	0.598 ± 0.160	35.000 ± 2.309
3	591.30 ± 8.525	0.482 ± 0.047	38.7 ± 5.638
4	589.70 ± 12.841	0.512 ± 0.120	39.100 ± 3.872
5	581.10 ± 11.090	0.461 ± 0.047	36.300 ± 3.368
6	583.50 ± 3.923	0.594 ± 0.254	35.000 ± 2.582
7	587.00 ± 7.394	0.542 ± 0.197	37.000 ± 4.163
8	586.20 ± 9.716	0.514 ± 0.078	37.000 ± 4.163
9	586.30 ± 5.250	0.517 ± 0.148	34.700 ± 1.160
10	581.10 ± 11.090	0.462 ± 0.040	35.700 ± 2.908
Average	587.86	0.52	36.44

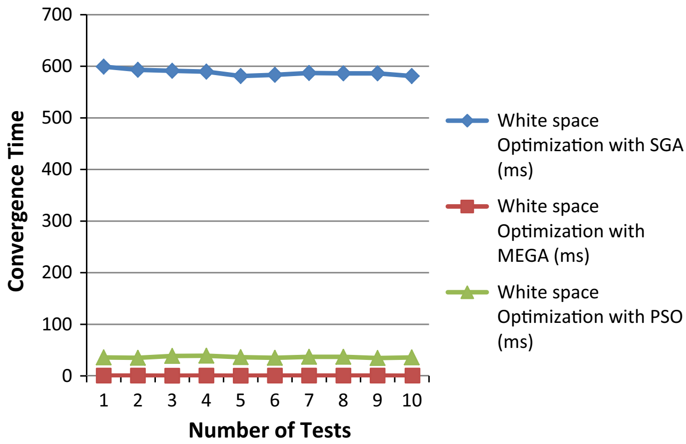

Fig. 6 Comparison of different convergence in terms of CPU times of simple genetic algorithm (SGA), MEGA and PSO

standard deviation of ±7.617, 35.900 ms with standard deviation of ±2.234 for PSO algorithm, and 0.556 ms with standard deviation of ±0.107 for the proposed approach using MEGA for test case 1 (Table 7). Also, for test case 7, genetic algorithm takes 587.00 ms, PSO algorithm converges after 37.000 ms standard deviation of ±4.163, and MEGA consumes 0.542 ms with standard deviation of ±0.197. The experimental results demonstrate that the proposed method using MEGA performs better in terms of CPU convergence time in comparison to genetic algorithm and PSO. The comparative chart of three optimization algorithms has been drawn in Fig. 6. The average whitespace optimization time for GA, MEGA and PSO are respectively found to be 587.10, 0.52 and 36.44 ms.

5 Conclusion

The existing RANs (GSM/GPRS, CDMA) in urban areas are overburdened to support new IVC networks. Existing cognitive radio based IVC systems are single-RAT based and may become less efficient. The proposed Multi-RAT based IVC system using cognitive frame work is a new approach towards deploying new IVC system without overburdening the existing RANs and is found to be more efficient in bandwidth utilization. The approach introduces the CR-Site within a vehicle which interacts with multi-RATs and optimizes the white space by performing multi-channels scanning. Users with different QoS requirements can be served using multi-RAT white space pool in CR-Site. The proposed approach solves the issue of sudden signal loss due to the use of single-RAT in hilly areas and ensures better bandwidth utilization of the existing radio networks by making use of memory enabled genetic algorithm. The algorithm is tested in real time for inter-vehicle communication system and is found to be beneficial than the fixed radio based IVC systems in hilly area of Mirpur in Azad Jammu Kashmir.

References

1. Toroyan, T., & Peden, M. (Eds.). (2007). *Youth and road safety*. Geneva: World Health Organization.
2. Patton, G. C., Coffey, C., Sawyer, S. M., Viner, R. M., Haller, D. M., Bose, K., et al. (2009). Global patterns of mortality in young people: A systematic analysis of population health data. *The Lancet, 374*(9693), 881–892.
3. Fink, D. A. (2014). The Prevention of road accidents in the countries of Europe, Asia and the United States of America. *World Applied Sciences Journal, 30*(12), 1863–1869.
4. Traffic accidents—Pakistan Bureau of Statistics. http://www.pbs.gov.pk/sites/default/files/social_statistics/crime_statistics/traffic_accidents.pdf. Accessed on 9 September 2015.
5. Foss, R. D., & Goodwin, A. H. (2014). Distracted driver behaviors and distracting conditions among adolescent drivers: Findings from a naturalistic driving study. *Journal of Adolescent Health, 54*(5), S50–S60.
6. Rumschlag, G., Palumbo, T., Martin, A., Head, D., George, R., & Commissaris, R. L. (2015). The effects of texting on driving performance in a driving simulator: The influence of driver age. *Accident Analysis and Prevention, 74*(2015), 145–149.
7. Chan, M., & Singhal, A. (2013). The emotional side of cognitive distraction: Implications for road safety. *Accident Analysis and Prevention, 50*, 147–154.
8. Lansdown, T. C., Stephens, A. N., & Walker, G. H. (2015). Multiple driver distractions: A systemic transport problem. *Accident Analysis and Prevention, 74*, 360–367.
9. Kumar, K., Prem, S., Evangelin, J., Amudharani, V. A, Inbavalli, P., Suganya, R., & Prabu, U. (2015). Survey on collision avoidance in VANET. In *Proceedings of the 2015 international conference on advanced research in computer science engineering & technology (ICARCSET 2015)* (p. 46).
10. Reddy, Y. B. (2015). Security and design challenges in cyber-physical systems. In *Information technology-new generations (ITNG), 2015 12th IEEE international conference* (pp 200–205).
11. Rawat, D. B., Bajracharya, C., & Yan, G. (2015). Towards intelligent transportation Cyber-Physical Systems: Real-time computing and communications perspectives. *SoutheastCon, 2015*, 1–6.
12. Riaz, F., Shah, S. I., Raees, M., Shafi, I., & Iqbal, A. (2013). Lateral Pre-crash sensing and avoidance in emotion enabled cognitive agent based vehicle-2-vehicle communication system. *International Journal of Communication Networks and Information Security (IJCNIS)*, *5*(2), 127–140.
13. Tae, OH., Choi, Y. B., Guthrie, M., Harold, K., Copeland, D., & Kim, T. H. (2010). Reeling in cognitive radio: The issues of regulations and policies affecting spectrum management. *International Journal of Future Generation Communication and Networking, 3*(3), 71–79.
14. Chávez-Santiago, R., Szydełko, M., Kliks, A., Foukalas, F., Haddad, Y., Nolan, K. E., Kelly, M. Y., Masonta, M. T., & Balasingham, I. (2015). 5G: The convergence of wireless communications. *Wireless Personal Communications 83*(3), 1617–1642.
15. Mishra, S.M., Sahai, A., & Brodersen, R.W. (2006). Cooperative sensing among cognitive radios, communications. In *ICC '06. IEEE international conference, vol. 4* (pp. 1658–1663).

16. Mitola III, J. (1999). Cognitive radio for flexible mobile multimedia communications. In *IEEE International workshop on mobile multimedia communications (MoMuC'99)* (pp. 3–10). San Diego, November 15–17 1999.
17. Deb, K. (2001). *Multi-objective optimization using evolutionary algorithms* (Vol. 16). New York: Wiley.
18. Hauris, J.F. (2007). Genetic algorithm optimization in a cognitive radio for autonomous vehicle communications. In *Proceeding of the 2007 IEEE international symposium on computational intelligence in robotics and automation,* Jacksonville, FL, USA, June 20–23 2007.
19. Singh, S. K., Singh, G., Pathak, V., Roy, D., & Chandra, K. (2011). Spectrum management for cognitive radio based on genetics algorithm. arXiv preprint arXiv:1101.4445.
20. Siddique, T. (2010). Spectrum optimization in cognitive radio networks using genetic algorithms. M.S Eletrical Engeneering. Thesis, Blekinge Institute of Technology, Sweden.
21. Chen, S., & Wyglinski, A. M. (2009). Cognitive radio-enabled distributed cross-layer optimization via genetic algorithms. In *Cognitive radio oriented wireless networks and communications, 2009. CROWNCOM'09. 4th international conference* (pp. 1–6).
22. Garvey, J. (2008) Car crash warning system could prevent the accident waiting to happen. http://www.gizmag.com/car-crash-warning-systemcould-prevent-the-accident-waiting-to-happen/8610. Accessed on 9 September 2015.
23. Jiang, D., & Delgrossi, L.(2008). IEEE 802.11p: Towards an international standard for wireless access in vehicular environments. In *IEEE vehicular technology conference, 2008. VTC spring 2008*, 11–14 May 2008.
24. IEEE Std 802.11p/D7.0. (2009). Wireless LAN medium access control (MAC) and physical layer (PHY) specifications: Wireless access in vehicular environment.
25. IEEE Std 1609.4-2006. (2006). IEEE trial-use standard for wireless access in vehicular environments (WAVE)—Multi-channel operation.
26. Wang, Z., & Hassan, M. (2008). How much of DSRC is available for non-safety use? In *Proceedings of ACM VANET*, San Francisco (pp. 23–29).
27. Noraini, M. R., & Geraghty, J. (2011). Genetic algorithm performance with different selection strategies in solving TSP. In *Proceedings of the world congress on engineering 2011 Vol II WCE 2011*, July 6–8, 2011, London, U.K.
28. Ghandour, A.J., Fawaz, K., & Artail, H. (2011). Data delivery guarantees in congested Vehicular ad hoc networks using cognitive networks. In *Proceedings of 2011 7th international wireless communications and mobile computing conference (IWCMC),* 4–8 July 2011 (pp. 871–876).
29. Ferreira, J., Fonseca, J., & Alves, J.A. (2012). Wireless vehicular communications for automatic incident detection and recovery. In *Proceedings of portuguese conference on automatic control—CONTROLO,* Funchal, Portugal (pp. 339–344).
30. Hassanzadeh, H. (2008) Reliable broadcast of safety messages in vehicular Ad hoc networks. Master thesis, Department of Electrical and Computer Engineering, University of Toronto.
31. Fawaz, K., Ghandour, A., Olleik, M., & Artail, H. (2010) Improving reliability of safety applications in vehicle Ad hoc networks through the implementation of a cognitive network. In *IEEE ICT, Doha, Qatar.*
32. Eichler, S. (2007). Performance evaluation of the IEEE 802.11p WAVE communication standard. In *IEEE 66th vehicular technology conference*, September 30–October 3 2007 (pp. 2199–2203).
33. Tsertou, A., & Laurenson, D. I. (2008). Revisiting the hidden terminal problem in a CSMA/CA wireless network. *IEEE Transactions on Mobile Computing, 7*(7), 817–831.
34. Bilstrup, K., Uhlemann, E., Strom, E. G., & Bilstrup, U. (2008). Evaluation of the IEEE 802.11p MAC method for vehicle-to-vehicle communication. *IEEE VTC Fall, 2008*(21–24), 1–5.
35. Wang, S. Y., Chao, H. L., Liu, K. C., He, T. W., Lin, C. C., & Chou, C. L. (2008). Evaluating and improving the TCP/UDP performances of IEEE 802.11(p)/1609 networks. In *Proceedings of IEEE Symposium on Computers and Communications*, (pp. 163–168).
36. Di Felice, M., Chowdhury, K.R., & Bononi, L. (2010). Analyzing the potential of cooperative cognitive radio technology on inter-vehicle communication. In *Proceedings of the international conference on wireless days 2010 IFIP*, 20–22 October 2010 (pp. 1–6).
37. Lan, K. C., & Li, M. W. (2010) Feasibility study of using FM radio for data transmission in a vehicular network. In *Computer symposium (ICS), 2010 international*, 16–18 December 2010 (pp. 55–60).
38. Fawaz, K., Ghandour, A., Olleik, M., & Artail, H. (2010). Improving reliability of safety applications in vehicle ad hoc networks through the implementation of a cognitive network. In *IEEE 17th international conference on telecommunications* (ICT), 4–7 April 2010 (pp. 798–805).
39. Li, H., & Irick, D.K. (2010). Collaborative spectrum sensing in cognitive radio vehicular Ad Hoc networks: Belief propagation on highway. In *Vehicular technology conference (VTC 2010-spring), 2010 IEEE 71st*, 16–19 May 2010 (pp. 1–5).

40. Wang, X. Y., & Ho, P. H. (2010). A novel sensing coordination framework for CR-VANETs. In *IEEE transactions on vehicular technology, vol. 59, no. 4* (pp. 1936–1948).
41. Shagdar, O., Ohyama, T., Shirazi, M. N., Tang, S., Suzuki, R., Miura, R., Obana, S. (2009). Message dissemination in inter-vehicle CDMA networks for safety driving support. In *Vehicular technology conference, 2009. VTC spring 2009. IEEE 69th*, 26–29 April 2009 (pp. 1–5).
42. Ko, Y. F., Sim, M. L., & Nekovee, M. (2006). Wi-Fi based broadband wireless accessfor users on the road. *BT Technology Journal Archive, 24*(2), 123–129.
43. Mangel, T. (2012). Inter-vehicle communication at intersections: An evaluation of Ad-Hoc and cellular communication. PhD diseratation, KIT Scientific Publishing, 5 July 2012.
44. Buddhikot, M. M. (2010). Cognitive radio, DSA and Self-X: Towards next transformation in cellular networks. In *Proceedings of IEEE symposium. New frontiers in dynamic spectrum (DySPAN'10).*
45. Sachs, J., Marić, I., & Goldsmith, A. (2010) Cognitive cellular systems within the TV spectrum. In *IEEE symposium on new frontiers in dynamic spectrum, IEEE 2010*, (pp. 1–12).
46. Cabric, D., Mishra, S. M., & Brodersen, R. W. (2004). Implementation issues in spectrum sensing for cognitive radios. In *Proceedings of Asilomar conference on signals, systems and computers (ACSSC), Pacific Grove*, California, USA (pp. 772–776).
47. Ganesan, G., & Li, Y. (2005). Agility improvement through cooperative diversity in cognitive radio. In *Global telecommunications conference, 2005. GLOBECOM '05.IEEE, vol. 5*, 2–2 December 2005 (p. 5).
48. Bhargavi, D., & Murthy, C. R. (2010). Performance comparison of energy, matched-filter and cyclo-stationarity-based spectrum sensing. In *IEEE eleventh international workshop on signal processing advances in wireless communications (SPAWC)*, 20–23 June 2010 (pp. 1–5).
49. Yuan, Y., Bahl, P., Chandra, R., Chou, P. A., Ferrell, J. I., Moscibroda, T., Narlanka, S., & Wu, Y. (2007) KNOWS: Cognitive radio networks over white spaces. In *Proceedings of IEEE international symposium on new frontiers in dynamic spectrum access networks*, Dublin, Ireland (pp. 416–427).
50. Yang, Y., Jiang, H., Liu, C., & Lan, Z. (2012). Research on cognitive radio engine based on genetic algorithm and radial basis function neural network, In *2012 Spring congress on proceedings of engineering and technology (S-CET)*, 27–30 May 2012 (pp. 1–5).
51. Wen, K., Fu, L., & Li, X. (2012). Genetic algorithm based spectrum allocation for cognitive radio networks. *Advances in Computer, Communication, Control and Automation Lecture Notes in Electrical Engineering, 121*, 693–700.
52. Xu, G., Tan, X., Ma, L., & Anghuwo, A. A. (2009). A construction algorithm of cognitive radio network with multiobjective genetic algorithm. In *Proceedings of IEEE youth conference on information, computing and telecommunication, 2009. YC-ICT '09*, 20–21 September 2009 (pp. 122–125).
53. Tang, P., & Lee, G. K. (2006). An adaptive fitness function for evolutionary algorithms using heuristics and prediction. In *Proceedings of automation congress, 2006. WAC '06. world* (pp. 1–6).
54. Chuang, Y. C., & Chen, C. T. (2011). A study on real-coded genetic algorithm for process optimization using ranking selection, direction-based crossover and dynamic mutation. In *Proceedings of 2011 IEEE congress on evolutionary computation (CEC)*, 5–8 June 2011 (pp. 2488–2495).
55. Noraini, M. R., & Geraghty, J. (2011) Genetic algorithm performance with different selection strategies in solving TSP. In *Proceedings of the world congress on engineering 2011 VolII WCE 2011*, July 6–8, 2011, London, U.K.
56. Eberchart, R., & Kennedy, J. (1995). Particle swarm optimization. In *Proceedings of IEEE international conference neural networks*, Perth, Australia (pp. 1942–1948).
57. Waheed, M., & Cai, A. (2009). Evolutionary algorithms for radio resource management in cognitive radio network. In *Proceedings of. 28th IEEE international conference on performance computing and communcations, 2009*, Arizona, USA.
58. Mahdi, A. H., Mohanan, J., Kalil, M., & Mitschele-Thiel, A. (2012). Adaptive discrete particle swarm optimization for cognitive radios. ICC, 6550–6554.
59. Wang, Y., Zhang, Q., Zhang, Y., & Chen, P. (2011). Adaptive resource allocation for cognitive radio networks with multiple primary networks. *EURASIP Journal on Wireless Communications and Networking,*. doi:10.1186/1687-1499-2012-252.
60. Juang, C. F. (2004). A hybrid of genetic algorithm and particle swarm optimization for recurrent network design. *In IEEE transactions on systems, man, and cybernetics—Part B: Cybernetics, vol. 34, no. 2.*

Faisal Riaz is a Doctoral student at Iqra University Pakistan. His research interests are Vehicular Cyber Physical Systems, Cognitive Radio, Affective Computing, and Agent Based Modelling. He has more than 24 research publications in various national/international research journals and conferences. He is heading Intelligent Transport Systems Lab at Mirpur University of Science and Technology (MUST), AJ&K Pakistan.

Imran Shafi received the Bachelor degree from the National University of Sciences and Technology (NUST) Pakistan in 1999 in Aeronautical Engineering, and the M.S. and Ph.D. degrees from Centre for Advanced Studies in Engineering (C@SE), University of Engineering and Technology (UET) Taxila Pakistan, in 2003 and 2009, respectively, in Computer Engineering. He has certificates Advanced Computer Networks and Databases from Stanford University California USA in 2011 and 2012 respectively. He has numerous papers in International peer-reviewed scientific journals and conferences. He is serving as a reviewer for prestigious IEEE, IET, Elsevier, Springer and Hindawi journals and conferences. His research interests are in the fields of cognitive radio, neural networks and digital signal processing.

Sohail Jabbar completed his MS (Telecom and Networking) with the honor of magna cum laude from Bahria University, Islamabad in 2009 and BS(Computer Science) from Allama Iqbal Open University in 2005. He has almost 7 years of teaching and research experience. He earned best researcher award of the year 2014 from Bahria University. He is also awarded research productivity award from COMSATS Institute of Information Technology in 2014. He has more than 30 research publications in various renewed journals and conference proceedings. He has also been the reviewer of number of SCIE Indexed Journals. He is an active member of Bahria University Wireless Research Center (BUWRC). Currently, he is serving as Lecturer at department of Computer Science, COMSATS Institute of Information Technology, Sahiwal, Pakistan. His research interests include Wireless Sensor Networks, Machine to Machine communication and Internet of Things.

Shehzad Khalid Ph.D. is a Professor and Head of Department at Department of Computer Engineering, Bahria University, Pakistan. He is a qualified academician and researcher with more than 50 international publications in conferences and journals. Dr. Shehzad has graduated from Ghulam Ishaq Khan Institute of Engineering Sciences and Technology, Pakistan, in 2000. He received the M. Sc. degree from National University of Science and Technology, Pakistan in 2003 and the Ph.D. degree from the University of Manchester, U.K., in 2009. Dr. Shehzad is the Head of Computer Vision and Pattern Recognition (CVPR) research group which is a vibrant research group undertaking various funded research projects. His areas of research include but are not limited to Machine Learning, Shape analysis and recognition, Motion based data mining and behavior recognition, Medical Image Analysis, ECG analysis for disease detection, Biometrics using fingerprints, vessels patterns of hands/retina of eyes, ECG, Urdu stemmer development, Short and Long multi-lingual text mining, Urdu OCR, Wireless sensor networks etc.

Seungmin Rho Ph.D. is a faculty of Department of Multimedia at Sungkyul University in Korea. In 2012, he was an assistant professor at Division of Information and Communication in Baekseok University. In 2009–2011, he had been working as a Research Professor at School of Electrical Engineering in Korea University. In 2008–2009, he was a Postdoctoral Research Fellow at the Computer Music Lab of the School of Computer Science in Carnegie Mellon University. He gained his B.Science. (2001) in Computer Science from Ajou University, Korea (South), M.Science. (2003) and Ph.D. (2008) in Information and Communication Technology from the Graduate School of Information and Communication at Ajou University. He visited Multimedia Systems and Networking Lab. in Univ. of Texas at Dallas from Dec. 2003 to March 2004. Before he joined the Computer Sciences Department of Ajou University, he spent 2 years in industry. His current research interests include database, big data analysis, music retrieval, multimedia systems, machine learning, knowledge management as well as computational intelligence. He has published more than 200 papers in refereed journals and conference proceedings in these areas. He has been involved in more than 20 conferences and workshops as various chairs and more than 30 conferences/workshops as a program committee member. He has been appointed as an Editor-in-Chief in Journal of Platform Technology (JPT) since 2013. He has edited a number of international journal special issues as a guest editor, such as Enterprise Information Systems, Multimedia Systems, Information Fusion, ACM Transactions on Embedded Computing, Journal of Real-Time Image Processing, Future Generation Computer Systems, Engineering Applications of Artificial Intelligence, New Review of Hypermedia and Multimedia, Multimedia Tools and Applications, Personal and Ubiquitous Computing, Telecommunication Systems, Ad Hoc & Sensor Wireless Networks and etc. He has received a few awards including Who's Who in America, Who's Who in Science and Engineering, and Who's Who in the World in 2007 and 2008, respectively.