Research Journal of Applied Sciences, Engineering and Technology 7(12): 2545-2553, 2014
DOI:10.19026/rjaset.7.565
ISSN: 2040-7459; e-ISSN: 2040-7467

Submitted: August 21, 2013 Accepted: September 03, 2013 Published: March 29, 2014

Research Article

An Efficient Dynamic Orthogonal Variable Spreading Factor Code Allocation Approach in WCDMA through Modified Adaptive Genetic Algorithm

[1]P. Kavipriya and [2]C. Gomathy
[1]Department of ECE, Sathyabama University, Chennai-600 119, Tamilnadu, India
[2]SRM University, Chennai, Tamilnadu, India

Abstract: Orthogonal Variable Spreading Factor (OVSF) codes would give variable data rate transmissions for different bandwidth supplies in Wideband CDMA (WCDMA) networks. These OVSF codes are used for the channelization of codes in WCDMA. In WCDMA, effective utilization of OVSF codes has become an active area of research as the number of codes is very limited. It is a fact that the successor and predecessor codes of OVSF cannot be used simultaneously when a specific code is used in OVSF as their encoded sequences become indistinguishable. Consequently, OVSF code tree has inadequate number of available codes. Thus, this research study uses Adaptive Genetic Algorithm (AGA) based approach for dynamic OVSF code assignment in WCDMA networks. Different from existing Conventional Code Assignment (CCA) and dynamic code assignment schemes, population is adaptively constructed according to existing traffic density in the OVSF code-tree. In existing technique in order to improve the ability of the GA, ''dominance and diploidy'' structure is employed to adapt to changing traffic conditions. Because in SGA algorithm cannot convergence if the new user is included into the existing OVSF code tree while SGA is running to find optimum OVSF code tree, SGA cannot adapt its structure to this unexpected variation. This problem can be overcome by the Modified Adaptive Genetic Algorithm (MAGA). Performance of the proposed MAGA approach is evaluated in terms of blocking probability and spectral efficiency and is compared with SGA, D&D GA.

Keywords: Adaptive genetic algorithm, Call Admission Control (CAC), Code-Division Multiple Access (CDMA), dynamic code assignment

INTRODUCTION

In Code Division Multiple Access (CDMA) mobile cellular systems, all downlink channels transmitted from the same Base Station (BS) are spread by different orthogonal codes to maintain orthogonality (Razavizadeh, 2008). Since the occupied transmission bandwidth is held to be invariable for different data rates, the variations in transmission data rates are accomplished by applying different lengths of orthogonal codes, referred to as Orthogonal Variable Spreading Factor (OVSF) codes. The number of available orthogonal codes is restricted to the code length and thus, efficiently utilizing OVSF codes becomes a significant issue. The code blocking problem is overcome by OVSF code relocation of existing users performed to leave a branch with the required rate for the requesting user (Yuh-Ren and Li-Cheng, 2009). This code relocation resolve to use the limited computational power hence the number of code relocation have to be reduced. To find the optimal branch to be leaved, the Dynamic Code Assignment (DCA) algorithm, which can reduce the number of OVSF code relocations is explained (Huan *et al*., 2012). Then again, code assignment and reassignment approaches are there to secure the presence of code blocking and the resultant code allocation is explained in (Balyan and Saini, 2010). Generally, the code assignment approach is built with a Call Admission Control (CAC) policy to guide to a complete solution (Wenlong *et al*., 2009). It is observed from the literature that the application of Genetic Algorithm (GA) for OVSF code assignment has given good results with a random initial population. However, the main issue in GA is the readaptation of GA to new atmosphere after convergence of its population (Xiaoling *et al*., 2013). It becomes difficult to handle the new reallocation problem once the code tree structure gets altered. Thus, the main drawback in GA is that the optimum solution cannot be attained for the previous code tree scenario. In order to eliminate the above said problem, diploid individuals and a dominance relation has been used by Mustafa and Adnan (2009) which act

Corresponding Author: P. Kavipriya, Department of ECE, Sathyabama University, Chennai-600 119, Tamilnadu, India

together to store traits that become useful when there are alterations in the environments (De Miguel *et al*., 2009). This research study focuses on providing significant results for the OVSF code assignment using a heuristic algorithm. Though, GA has been observed to produce good results however, problems of convergence and prematurity occurred in GA. This study presents an efficient GA called Modified Adaptive Genetic Algorithms (MAGA) algorithm for the purpose of OVSF code assignment, which could adjust the parameters adaptively based on the value of individual fitness and dispersion degree of population.

OVSF CODE TREE

Layer k has 2^k codes and they are consecutively labeled from left to right path, starting from one. The m^{th} code in layer k is denoted to code (k, m) In each layer the total capacity of all the codes is 2^kR, it is irrelevant of the layer number. Also define the maximum spreading factor $N_{max} = 2^k$ as the total number of codes in layer K. The maximum capacity of the system is expressed as ccapacity = 2^k R where K denotes the highest layer of the tree and R represents the fundamental data rate is shown in the Fig. 1.

After a process period, available codes will be spread out around the code tree. This random spread out of the available codes within the code tree is called fragmentation which in turn results in code blocking. This would greatly affect the performance of the system.

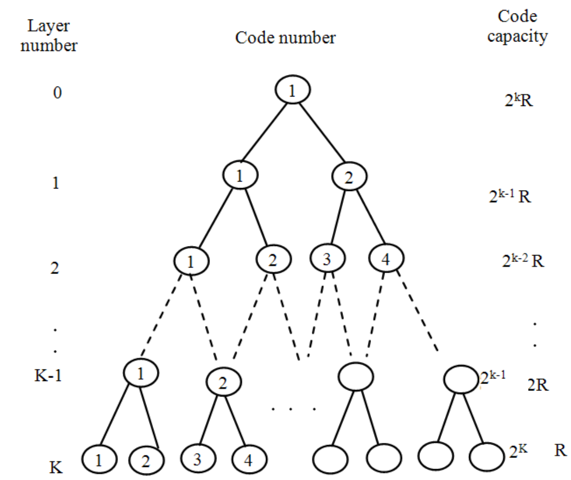

Fig. 1: OVSF code tree

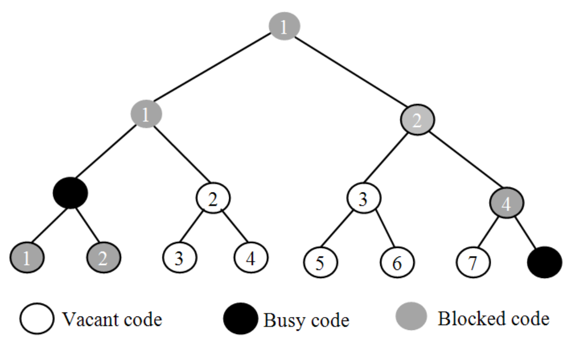

Fig. 2: Code blocking scenario

Code blocking scenario: Code blocking is the major limitation of OVSF-CDMA system. Code blocking is phenomena in which a call or session is blocked even though the system has adequate capacity to support the rate necessity of the call or session. In Fig. 2, code tree with four layers is taken into consideration. The maximum capacity of the code tree is 8R in the code tree, two codes with SF4 (for data rate 2R) and 8 (for data rate R) are occupied. Hence, the capacity used for the OVSF code is 3R. The remaining capacity of the code tree is 8R-3R = 5R. If a new call with data rate 4R arrives, code from the third layer is needed. The code tree is not capable to offer code for the new call, as both the codes equivalent to 4R capacity is blocked. Thus, this is a scenario in which a new call cannot be supported even if the system has adequate capacity to deal with. This scenario called code blocking has to be avoided through efficient and optimized assignment and reassignment schemes (Davinder and Neeru, 2010).

Heuristic approaches in OVSF code allocation: Genetic algorithm is a heuristic approach which is observed to provide significant results in optimization problems (Mehmet *et al*., 2012). This section discusses this reallocation process starting based on heuristic algorithms to make OVSF code assignment strategy. Execution is not essential for resource assignment in idle state. Call is started with the call processor's signaling to resource manager to assign resources for a traffic channel. Initially, availability of capacity is enquired in the code tree in order to make a decision whether to support the requested call rate in the system. If there is adequate capacity, then availability of requested rate OVSF code is checked among unused codes in the relevant layer, where the call can be supported (Karakoc and Kavak, 2009). If a call cannot be assigned a code due unavailability of the code with the requested rate (or all supported codes for this rate are not orthogonal to the assigned codes), GA block is executed. In the GA block, reassignment process of OVSF codes is performed.

The attribute of the GA mostly is based on the selection and determination of crossover probability and the mutation probability (Jiang and Meng, 2012). The major drawbacks of GA are slow convergence, prematurity and moreover it lacks rank based fitness function which reduces complexity. Adaptive Genetic Algorithm (AGA) is observed to produce better results than GA. But, the adaptive genetic algorithm also has some drawbacks which would affect the performance of the system to a great extent.

PROPOSED IMPROVEMENT IN ADAPTIVE GENETIC ALGORITHM

Improvement in the GA is presented in order to overcome the above said issues.

In order to have higher convergence speed, it is essential to make the population relatively rapid shift to the optimal state. This will minimize the population diversity. Eliminating the early trapping of local optimum, determining optimal solutions rapidly in the same time and to avoid premature convergence of GA are not easy. Parameter selection in SGA and AGA causes in early maturity and local optimization problem which results in the premature loss of population diversity. Improvement in the AGA is presented to handle the above said issue.

Evaluation of population diversity: Generally the size of population is obtained, when the diversity of population is greater, it will result in better generation (Jiang and Meng, 2012). Evaluation of population entropy is an indicator of population diversity.

A set p (t) witht the generation population and N population size is considered. Based on various types of individuals into m parts, P_1 (t), P_2 (t), P_3 (t) …. P_m (t) it is clear that $\bigcup_{i=1}^{m} p_i(t) = p\ (t)$ for $\forall$i, j $\in$ {1, 2,.., m} there are P_i (t) $\cap P_j$ (t) = $\varnothing$. Set k_1, k_2….k_m are the size of P_1 (t), P_2 (t), P_3 (t) …. P_m (t), then $\sum_{i=1}^{m} k_i = N$. Delimit the value of population entropy of the t generation is $E = -\sum_{i=1}^{m} p_i log p_i$ where $p_i = k_i/N$. From the formulation of entropy, when the individuals in the population are different from each other, that is m = N, the value of entropy attains the maximum E_{max} = log N and vice versa. Entropy would be maximum when the different types of individual population have even distribution. The value of population entropy will alter with the change in the diversity of population. Comparing the value of current population entropy and the maximum value, the diversity of contemporary populations is evaluated. Set $a = E_t/E_{max}$ and $a \in [0, 1]$.

If the value of a is larger, then the number of different individuals in the current population is also greater or vice versa. The ability of population to search the better individuals would be efficient when the population diversity is higher. When a is smaller; the ability of population to search the better individuals is weaker. Thus, the mutation probability should be increased to increase population diversity and then phenomenon of local optimization should be avoided (Wang *et al*., 2010).

Improvement of crossover and mutation probability: According to population entropy, the crossover probability and mutation probability is altered in the following steps.

According to the diversity of contemporary populations (i.e., population entropy), probability ranges are determined:

$$\begin{cases} p_{c1}(t) = p_{c1} + \dfrac{(p_{c2} - p_{c1})}{2} * a_t \\ p_{c2}(t) = p_{c2} - \dfrac{(p_{c2} - p_{c1})}{2} * (1 - a_t) \end{cases}$$

where, p_{c1}, p_{c2} represents the ranges of the initial crossover probability and $p_{c2}>p_{c1}$; a_t denotes the tth population diversity. p_{c1} (t), p_{c2} (t) represents the range of crossover probability in tth generation population. In the above equation, a_t is larger, the crossover probability is larger. In the contrary, it is smaller:

$$\begin{cases} p_{m1}(t) = p_{m1} + \dfrac{(p_{m2} - p_{m1})}{2} * (1 - a_t) \\ p_{m2}(t) = p_{m2} - \dfrac{(p_{m2} = p_{m1})}{2} * a_t \end{cases}$$

where, p_{m1}, p_{m2} represents the range of initial mutation probability and $p_{m2}>p_{m1}$; a_1 denotes the tth population diversity p_{m1} (t), p_{m2} (t), represents the range of mutation probability in tth generation population. With the above equation, a_t is larger, the mutation probability is smaller. In the contrary, it is larger.

According to the range and the fitness value, the value of crossover and mutation probability is obtained:

$$p_c = \begin{cases} \dfrac{p_{c1}(t)(f_{avg} - f') + p_{c2}(t)(f' - f_{min})}{f_{avg} - f_{min}} f' < f_{avg} \\ \dfrac{p_{c2}(t)(f_{avg} - f') + p_{c3}(t)(f' - f_{min})}{f_{max} - f_{avg}} f < f_{avg} \end{cases}$$

$$p_m = \begin{cases} \dfrac{p_{m1}(t)(f_{avg} - f') + p_{m2}(t)(f' - f_{min})}{f_{avg} - f_{min}} f < f_{avg} \\ \dfrac{p_{m2}(t)(f_{avg} - f') + p_{m3}(t)(f' - f_{min})}{f_{max} - f_{avg}} f < f_{avg} \end{cases}$$

where,

f_{max} : The maximum value of the population
f_{avg} : The average value of every generation population
f_{min} : The minimum value of the population
f' : The larger value in the two individuals to cross
f : The fitness value of the individual to mutate
$p_{c1}(t)$, $p_{c2}(t)$: The upper and lower limits of the crossover probability after the adjusting in the first step
p_{c3} (t) : A constant and $p_{c3}(t) < p_{c1}(t) < 1$
p_{m1} (t), $p_{m2}(t)$: The upper and lower limits of the mutation probability after the adjusting in the first step
$P_{m3}(t)$: A constant and $p_{m3}(t) < p_{m1}(t) < 1$ (Youchan and Feng, 2012)

Proposed Modified Adaptive Genetic Algorithm ()
initialize population;
evaluate diversity population;

```
while convergence not achieved
{
scale population fitness;
select solutions for next population;
perform improved crossover and mutation probability;
evaluate population;
}
}
```

Thus, Modified AGA (MAGA) is presented which improves the AGA through the evaluation of population diversity. Thus, the operation probability of the genetic algorithm is improved. Hence, it can be better to control the crossover and mutation probability based on the current population and adapts them based on the changes of fitness value.

Proposed dynamic OVSF code allocation using modified adaptive genetic algorithm: In this research study, in order to overcome the drawbacks of the SGA and AGA, MAGA is presented in this approach to have better code blocking probability. The flowchart of the proposed approach is given in Fig. 3. If a call cannot be allotted a code due to unavailability of the code with the requested rate then MAGA block is executed. In the MAGA block, reassignment process of OVSF codes is carried out. The OVSF code tree which is input to the MAGA block is called as initial chromosome (Chini) and this chromosome is denoted with the index number which belongs to active users in the given code tree (Chini = (6 9 14 16 21)).

Here in this approach the integer value is taken from the index numbers 1 to SF-1, allocated from root code which is indicated as index 1. Then the left descendant code is index 2, right descendant code is index 3, this is nonstop up to the lowest layer-rightmost branch. Each active user's index number in the initial chromosome is termed as a gene denoted by an integer number. The data bit rates of Chini in Fig. 3 are (4R 2R 2RRR) which is equivalent to the index numbers in the OVSF code tree. R represents the fundamental data rate needed for the transmission through the lowest layer codes in the code tree. The data rates are doubled as layer is getting topper in the code tree. Hence the root code needs SF×R rate transmission of data. The size of initial population which generated from chromosomes is defined according to Eq. (1) and depends on the traffic density which is:

$$n = SF - \sum_{i-1}^{V} H(i) \tag{1}$$

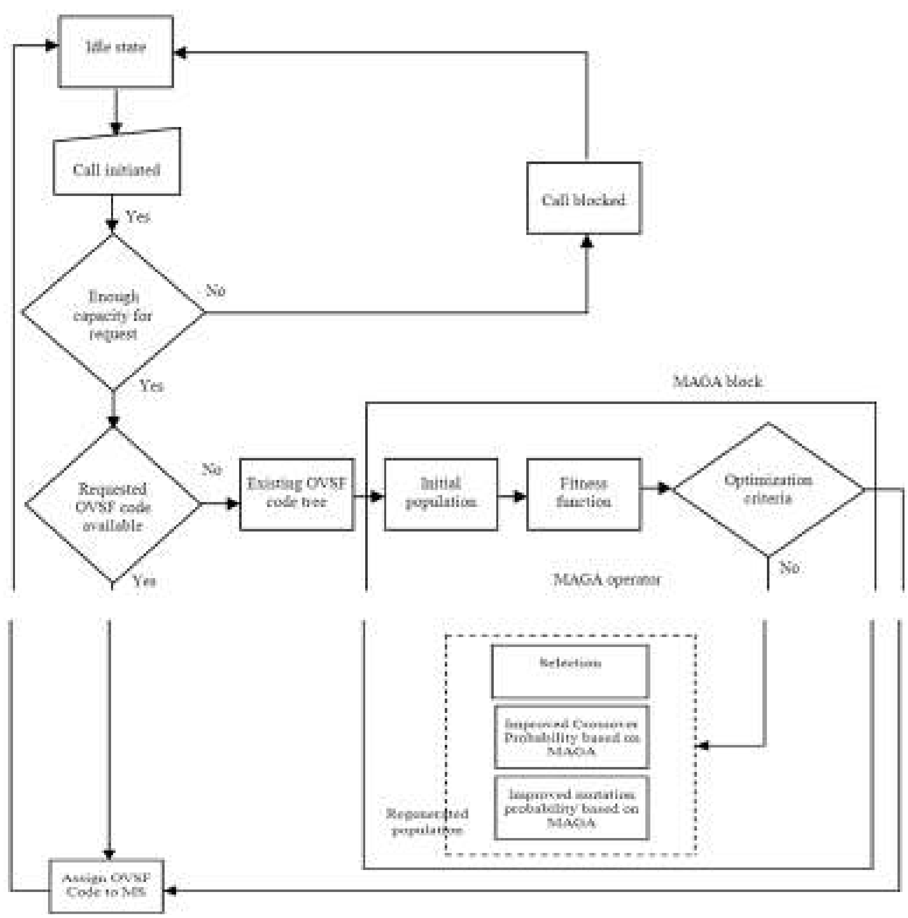

Fig. 3: Flowchart of OVSF code assignment system using MAGA block

where,
V = Total number of active users
H (i) = Date rate of i^{th} active user, i = 1…, V

V, H and SF are 5, 10 and 16, correspondingly. As a result the initial population (n) of the chromosome is attained as 6 (16-10). Initial population chromosome with various code tree index numbers other than the number of data bit rates of each chromosome is the same as initial chromosome. The n chromosomes consist of existing coded information of OVSF tree is attained by means of permutation and gives an optimized result for a problem.

Chini gives the first chromosome. 1st chromosome is obtained from the Chini. Temporary Population TP (1) which is obtained from Chini with random permutation is sequentially alloted to empty OVSF code tree from 1^{st} to 5^{th} gene. It is essential to take into consideration the orthogonality principle, while assigning codes in the OVSF code tree. Index numbers are taken to compose a new chromosome P (1). The process of attaining P (1) is as follows: for each gene of TP (1), the equivalent gene in P(1) is chosen as the possible leftmost OVSF code that has the same rate as this gene in TP (1). For example, the initial gene numbered by 14 in TP (1) has the rate 2R. Therefore, possible leftmost gene with rate 2R is the OVSF code numbered as 8 in P (1). P shows, several different possible result for a given problem. It is clear that iteration number of optimal solution is depends on population size (n), users' data bit rates (H (i)) and their location in the code tree. Then, the fitness value for each chromosome of population is evaluated according to fitness function, which is defined specially for OVSF code assignment-reassignment problem. The fitness value of jth chromosome f (j) is the quantity of replacement of each individual in P (j) according to Ch_{ini} defined by:

$$f(j) = \frac{1}{\sum_{i=1}^{V} (Ch_{ini}(j)) - P(j,i) \times H(i)} \tag{2}$$

where, j is the chromosome number, j = 1, …, n.
For, the gene numbered 21 with rate R in TP (1), we obtain the OVSF code numbered 18 and so on. After obtaining each corresponding gene for P (1), we list the genes in P (1) from highest rate to lowest rate. This process is repeated n times to fill the P.

The population is ensured for its fitness values. If an OVSF code tree denoted by best chromosome, can allocate the requested data bit rate to appropriate user, then optimization criterion is confirmed and requested data bit rate is allocated to desired user. If not, other chromosomes in the population are checked. The stopping criterion for this process is either run-on until to assign the requested data bit rate to a user or until the end of predetermined loop counter.

EXPERIMENTAL RESULTS AND EVALUATION

The main focus of this research is to enhance the number of free codes at OVSF code tree through reassignment of presently allotted codes. When the system still has adequate capacity to offer the data bit rate request and requested data bit rate cannot be supported since all available codes for this data bit rate are not orthogonal to the assigned codes, reassignment of OVSF code tree assist in determining the appropriate code to the demanding user. In order to evaluate the performance of the proposed code assignment approach using Modified Adaptive GA (MAGA), it is compared with SGA and D&D-GA by simulations.

Simulation parameters: For this simulation setup, a number of OVSF-concerned and GA-concerned parameters are used:

OVSF concerned parameters	
Mean arrival rate	4 to 64 calls/unit
Call duration	0.25 time units
Maximum SF	256
Possible OVSF code rates	Uniform distribution between R and $SF \times R$

Some of calls leave the system according to Exponential call duration. Active (served) calls of OVSF codes, GA parameters, number of assigned, blocked and reassigned users and their data rates are stored while the simulation is running. Karakoc and Kavak (2009) For the same input parameters, the simulations are repeated 10 times and the results for these 10 simulations are averaged. Then, regarding the GA-concerned parameters, a chromosome is represented by an integer number. Population size depends on the traffic density, in other words number of user in the system and their data bit rates. Effects of different selection, crossover and mutation techniques are investigated. Crossover rate pc is varied between 0.2 and 0.8, while mutation rate pm is varied between 0.05 and 0.2. The number of pre-determined loop for stopping criterion is 10,000.

Results: System performance of the algorithms are performed for SGA, D and D-GA and MAGA.

Blocking probability: Blocking probability is the ratio of the number of blocked calls (N_B) to total number of all incoming calls (N_T), given by:

$$\Pr(\text{blocking}) = \frac{N_B}{N_T}$$

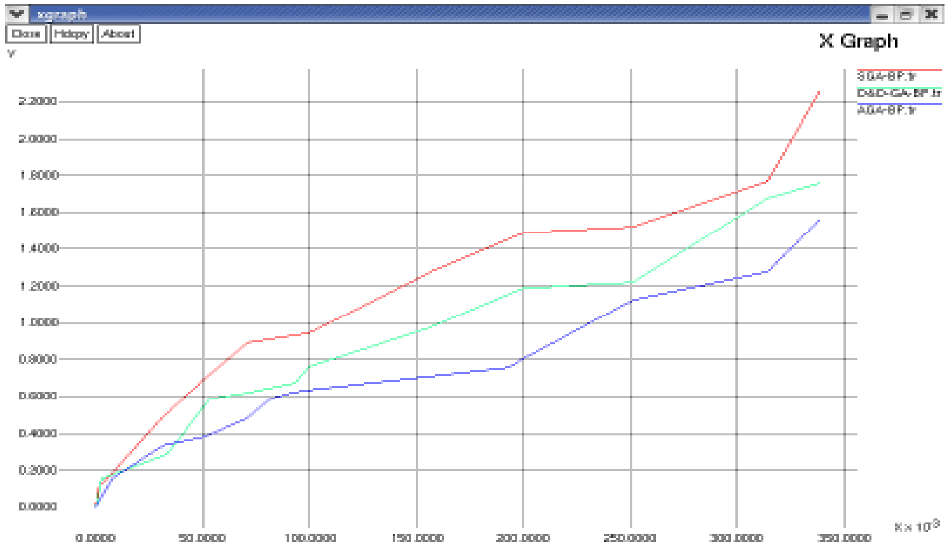

Fig. 4: Comparitive analysis of blocking probability

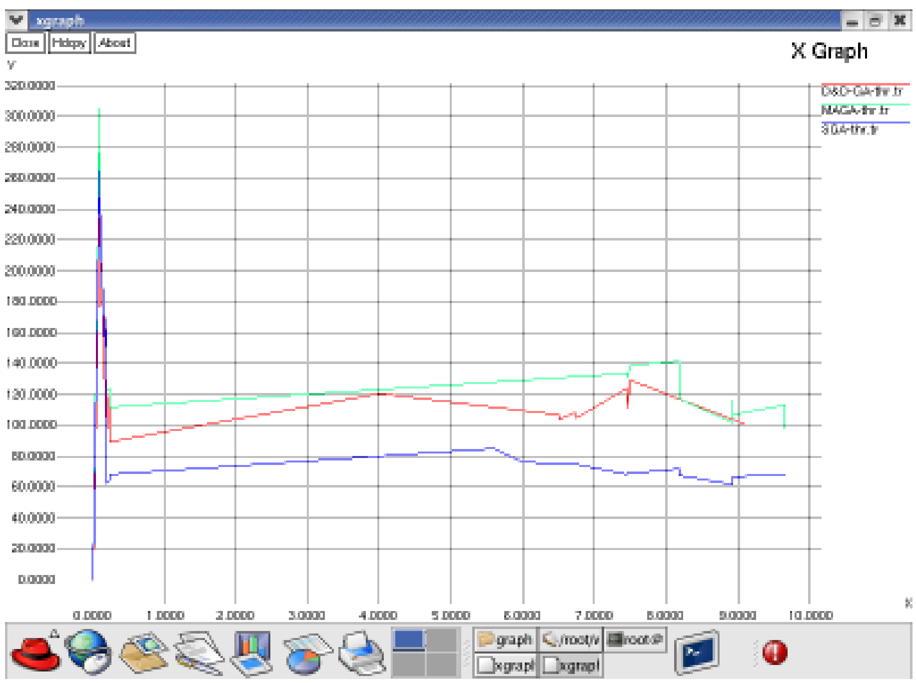

Fig. 5: Comparitive analysis of throughput

Figure 4 shows the results of our simulations for blocking probability at different traffic loads when SF is 256. It is seen from figure that the proposed AGA performs better than D and D-GA which is followed by SGA, DCA and then CCA. For instance, AGA serves more call when it is compared with D and D-GA algorithm when traffic load is larger than 10. At higher loads, proposed algorithm performance improvement is more significant than D and DGA.

Spectral efficiency: Spectral efficiency is evaluated to measure the ratio of assigned data rate ($R_{assigned}$) over the total requested data rate ($R_{requested}$) of all incoming calls, which is given b:

$$\eta(\%) = \frac{K_{assigned}}{R_{requested}} \times 100$$

Code blocking probability focuses the number of users while spectral efficiency focuses this user' data bit rates. Figure 5 shows the spectral efficiency of the five methods at different traffic loads. The spectral efficiency of the resource is inversely proportional to

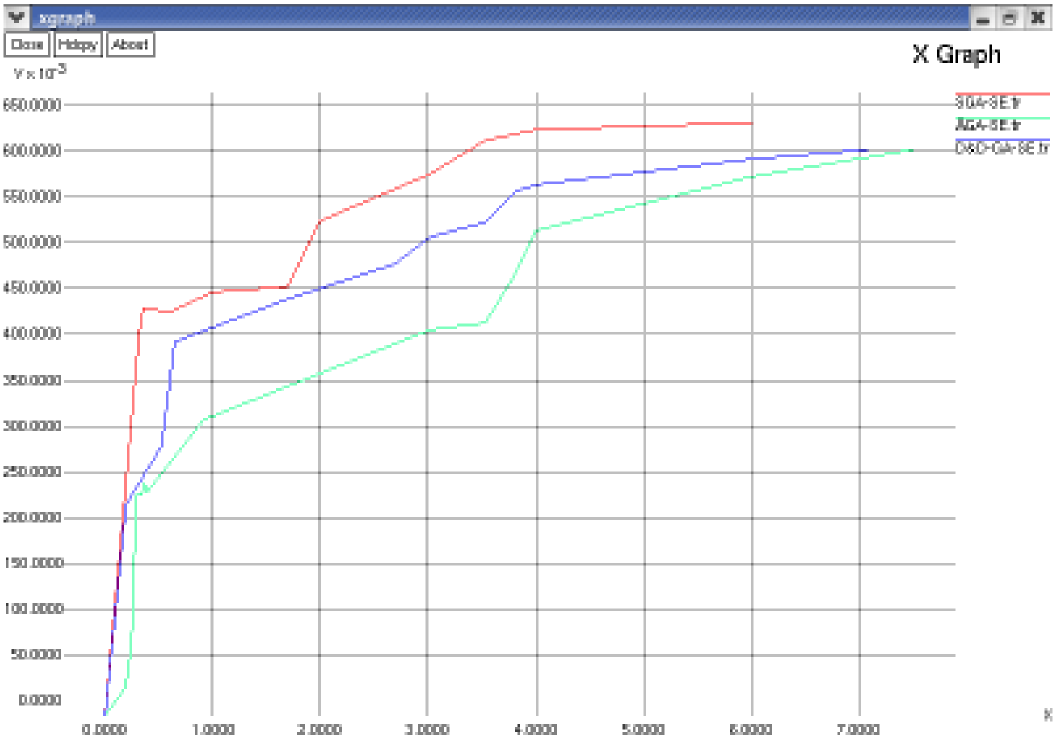

Fig. 6: Comparitive analysis of spetral efficiency

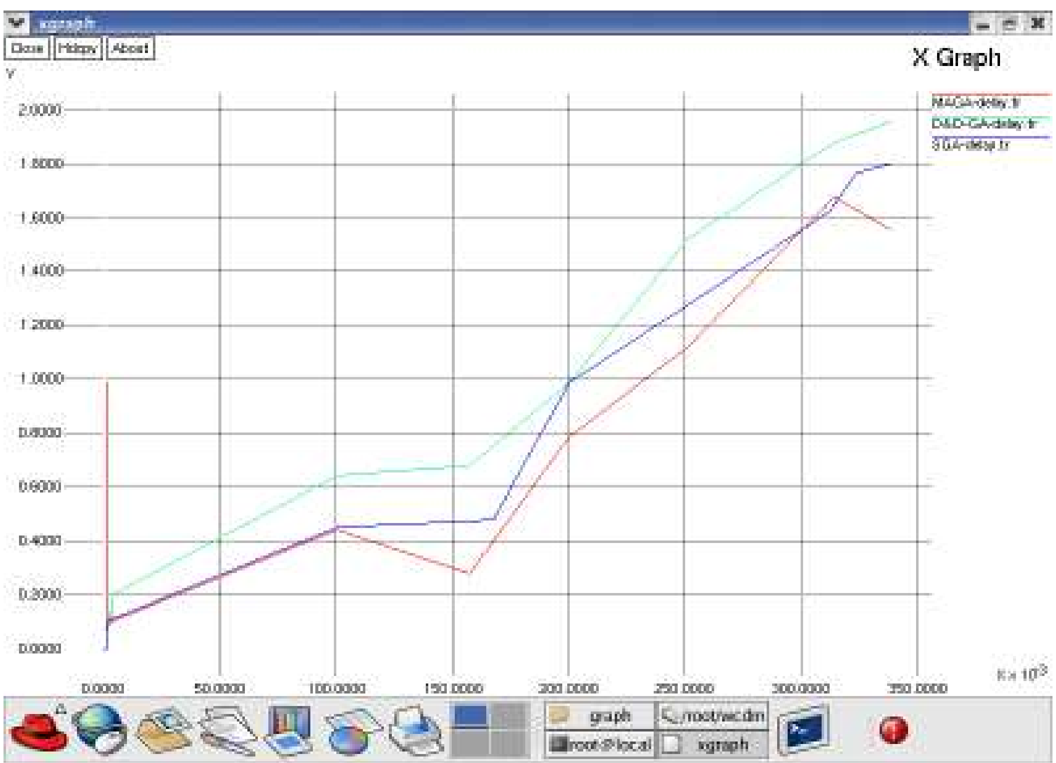

Fig. 7: Comparitive analysis of delay

the traffic load in the system. Clearly, proposed algorithm (AGA) provides the largest spectral efficiency among D&D-GA and SGA.

Figure 6 shows the spectral efficiency of the proposed approach compared with the other approaches.

Fig. 8: Comparitive analysis of drop ratio

Figure 7 shows the delay comparison of the approaches taken for consideration. It is observed from the graph that the proposed MAGA approach has lesser delay when compared with the D and D-GA and SGA approaches.

Figure 8 shows the comparison of the drop ratio of different techniques taken for consideration. It is observed from the figure that the drop ratio of the proposed MAGA approach is lesser than the other two approaches such as SGA and D&D GA.

Figure 5 shows the Through put of the proposed MAGA approach is very higher when compared with SGA and D&D GA. The graph shows that maximum throughput has been obtained for the proposed approach. It is mainly due to the improvement in mutation and crossover probability.

CONCLUSION

The orthogonality property of OVSF codes makes more appropriate for WCDMA. OVSF codes assignment have high influence on the code utilization and system performance. This research study utilizes an efficient heuristic algorithm namely Modified Adaptive Genetic Algorithm (MAGA) based dynamic OVSF code assignment for WCDMA systems in order to reduce the call blocking and increase the spectral efficiency in the system. The simulation results show that AGA provides the smallest blocking probability and largest spectral efficiency in the system when compared to SGA and D&D-GA. The future study of this approach would be to use meta heuristic optimization algorithm to seek better results in terms of call blocking and spectral efficiency.

REFERENCES

Balyan, V. and D.S. Saini, 2010. Immediate neighbor assignment and reduction in code blocking for OVSF-WCDMA. Proceeding of the IEEE International Conference on Software, Telecommunications and Computer Networks (SoftCOM), Sept. 23-25, pp: 155-159.

Davinder, S.S. and S. Neeru, 2010. An efficient multi code design for code blocking reduction in 3G wireless networks. Proceeding of the IEEE Sarnoff Symposium, April 12-14, pp: 1-5.

De Miguel, I., V. Reinaldo, A. Beghelli and R.J. Duran, 2009. Genetic algorithm for joint routing and dimensioning of dynamic WDM networks. J. Opt. Commun. Netw., 1(7): 608-621.

Huan, C., C. Chih-Chuan, C. Wei-Ho and Y. Hsi-Hsun, 2012. A reduced dimension MDP-based call admission control scheme for next generation telecommunications. Proceeding of the IEEE 8th International Wireless Communications and Mobile Computing Conference (IWCMC), Aug. 27-31, pp: 984-989.

Jiang, J. and L. Meng, 2012. The strategy of improving convergence of genetic algorithm. Telkomnika, 10(8): 2063-2068.

Karakoc, M. and A. Kavak, 2009. Genetic approach for dynamic OVSF code allocation in 3G wireless networks. Appl. Soft Comput., 9: 348-361.

Mehmet, E.A., K. Raymond, D. Wei and W. Joyce, 2012. A genetic algorithm approach for multiuser scheduling on the LTE downlink. Proceeding of the World Congress on Engineering, 2: 1.

Mustafa, K. and K. Adnan, 2009. Genetic approach for dynamic OVSF code allocation in 3G wireless networks. Appl. Soft Comput., 9: 348-361.

Razavizadeh, S.M., 2008. Cooperative diversity in downlink of cellular CDMA systems using maximum ratio precoding. Proceeding of the IEEE 14th Asia-Pacific Conference on Communications (APCC), Oct. 14-16, pp: 1-5.

Wang, P., J. Chen and F. Pan, 2010. An improvement genetic algorithm using Predatory search. J. Southeast Univ., Nat. Sci. Edn., Vol. 40.

Wenlong, N., L. Wei and M. Alam, 2009. Determination of optimal call admission control policy in wireless networks. IEEE T. Wirel. Commun., 8(2): 1038-1044.

Xiaoling, W., W. Yangyang, L. Guangcong, L. Jianjun, S. Lei, Z. Xiaobo, C. Hainan and L. Sungyoung, 2013. Energy-efficient routing algorithms based on OVSF code and priority in clustered wireless sensor networks. Int. J. Distrib. Sens. N., 2013: 8.

Youchan, Z. and S. Feng, 2012. An improvement adaptive genetic algorithm. Proceeding of the International Conference on Education Technology and Computer.

Yuh-Ren, T. and L. Li-Cheng, 2009. Quality-based OVSF code assignment and reassignment strategies for WCDMA systems. IEEE T. Veh. Technol., 58(2): 1027-1031.