Cognitive Control Based on Genetic Algorithm for Routing and Wavelength Assignment in Optical OBS/WDM Networks.

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Abstract - **The exponential services demand concerning the Information and Communications Technology (ICT) has led to increasingly efficient implementation techniques to satisfy the information flow required by users. Optical Burst-Switched Wavelength Division Multiplexing networks (OBS/WDM) are currently set as a technology capable of supporting wide bandwidth, allowing high information's transmission and different types of traffic. OBS also combines the advantages of Optical Circuit Switching (OCS) and Optical Packet Switching (OPS). Furthermore, recent advances in optical networking add cognitive mechanisms to any network plane, providing it with adaptive features. From this point of view, it is possible to carry out methods that address the problem of Dynamic Routing Wavelength Assignment (DRWA) in order to improve the network blocking probability. In this paper, we propose a cognitive control method, based on genetic algorithms for DRWA problems in OBS/WDM networks under wavelength continuity constraint, analyzing its performance in terms of blocking probability and execution time by making a comparison with the same network that uses genetic algorithms, but without cognitive control.**

***Keywords-** optical burst switching; dynamic routing and wavelength assignment; genetic algorithms; cognition.*

I. INTRODUCTION

The changes made during the last years in telecommunication networks are mainly based on the need to supply the traffic demand due to the exponential growth of the Internet and the Web evolution [1]. This implies having networks capable of supporting high bandwidth. For this reason, the optical fiber is becoming one of the most important means of transmission today. Moreover, among the advantages of optical networks is the ability to carry data simultaneously by the same fiber using different wavelengths; this technique is called Wavelength Division Multiplexing (WDM).

It is also expected that the current optical networks receive all traffic more efficiently. For this, switching techniques like Optical Burst Switching (OBS) are implemented due to its bandwidth capacity, low latency, high adaptability, and low processing overhead [2].

Before sending a burst through the network, it is divided into the Burst Control Packet (BCP) and data packet. The BCP is sent across a dedicated channel, and it is responsible for the burst's routing. On the other hand, the data packet will be sent only when a timeout has elapsed after sending the BCP. For this reason, the signaling used is out of band, allowing space-time separation between header and data, thus providing manageability and network resilience.

Dynamic Routing Wavelength Assignment (DRWA) in OBS/WDM (Optical Burst-Switched Wavelength Division Multiplexing networks) networks, implements methods for routing and wavelength assignment between links. Such process can be done between two nodes not necessarily adjacent, and requires an available wavelength and route between the optical paths. This connection is called lightpath, and due to the dynamic features, the requests to set it are made at real time.

However, as the DRWA is an Nondeterministic Polynomial Time Complete (NP-C) problem [3], is not possible to use deterministic algorithms for its solution, instead, different methods are proposed to obtain near optimal solutions. This kind of problem allows the use of Genetic Algorithms (GA) as heuristic methods for DRWA in OBS/WDM networks.

The GA resembles the evolution stages and natural selection mechanisms postulated by Charles Darwin. They work with individuals from a population, each representing a tentative solution to the problem. The main GA stages are: generation of individuals, selection, crossover, mutation, and reduction operators. The genetic algorithm will perform a number of iterations of the above stages, until one of the stopping criteria is met. An equally important factor when talking about GA corresponds to fitness function, whose objective is to assign a value to each individual, which measures the relevance of such solution to the problem being tackled. An appropriate fitness function guides the GA towards its goal, converging to optimal solutions.

Moreover, the search for increasingly flexible networks capable of supporting all types of traffic, transmission, and switching technologies, lead to intelligent network management through techniques that allow awareness and adaptation mechanisms at any optical architecture level. Cognitive control methods are a promising factor to meet the challenges the next-generation optical networks have [4][5].

Taking into account the information provided, this article uses two approaches based on GA to the DRWA problem in OBS/WDM networks, one of them using cognitive control methods.

To facilitate understanding, the article is organized as follows. In Section 2, we present the related work to the different topics involving the current research. The next section presents the model and the simulation tool used for

 ISBN: 978-1-61208-315-5

OBS/WDM networks. Sections 4 and 5 will focus on the DRWA problem from the perspective of GA. Then, in Section 6, the inclusion of a cognitive information base supported on GA is presented. Subsequently, we analyze the networks performance taking into account the blocking probability and processing time. Finally, conclusions will be shown in Section 8.

II. RELATED WORK

The aim of this paper encloses a context that unifies several study subjects. Related work about the RWA problem in OBS/WDM networks using cognitive control methods based on GA has not been widely developed. However, certain topics are treated in some research.

For example, Gond and Goel [6] and Gonzales et al. [7] solve the RWA in DWDM networks taking into account physical constraints and including devices called optical converters enabling the switching of wavelengths to increase efficiency. However, they don't use GA, OBS, or cognitive control methods in their strategies.

Kavian et al. [8] and Kavian [9], apply genetic algorithms to the RWA in WDM networks, including in cases like Nakkeeran, et al. [10], strategies of fairness among connections and fault tolerance capability. This papers present disadvantages because there is no evidence of the used switching method.

Moreover, Kozlovski [11], although the authors reflect routing and wavelength assignment strategies specifically in OBS/WDM networks, they don't use GA or cognitive control methods to solve de DRWA problem.

The approach of Tomkos et al. [12] focuses on cognitive optical networks towards a perspective that provides autonomy and counteracts the increasing complexity in the use and network performance. Finally, (and arguably one of the most similar to the one developed in this paper) Durán [13] proposes a strategy based on cognition to solve Impairment-Aware Virtual Topology Design Problems. Although the author does not focus on the switching technique used, he develops a GA including a memory-based cognitive control method to optimize the virtual topology design.

At the moment, there are no evidences of researches related to the DRWA problem in OBS/WDM networks using GA and cognitive control to analyze the network performance. Considering the above, this work aims to apply a cognition control method to an OBS/WDM network that implements GA for RWA processes and analyze the performance, comparing it with the same network that only uses GA for DRWA.

III. OBS/WDM NETWORK SIMULATION

In order to simulate an OBS/WDM network that enables the GA implementation, OMNeT++ [14] is chosen as the used tool since it has flexible, organized, and suitable software for the simulation of interconnection networks for high performance. To develop the network design, it must be noted that OBS works with two kinds of nodes. The first one is called Edge Node, and presents the following stages:

Assembler Module (EdgeNodeAssembler): it is responsible for assembling IP packets into bursts. To do this, it makes use of three submodules. The first one is the Classifier; the packets go across this module only if their destination and class of service are valid values to send through the network. The Burstifier is another submodule and performs package grouping tasks to form bursts; three assembly criteria are set: time, number, and packet length. Once the bursts are formed, the last submodule called Sender, is responsible for dividing them in BCP and data packet.

Disassembler Module (EdgeNodedisassembler): when the burst reaches its destination, is disassembled returning to the original packets. Figure 1 shows the Edge Node modules.

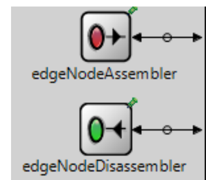

Figure 1. Edge Node modules.

The responsible for routing tasks and network planning is the Core Node (CoreNode). Inside of it are also several submodules:

The Input submodule (CoreInput) can differentiate between data packets and BCP to determine where to send them. If a burst arrives, then, is sent to the Core Control Unit (CoreControlUnit) by a dedicated cannel; moreover, if is a data burst, it will be sent to the Optical Switching Module (OXC) through which it pass in all optical way. Figure 2 shows the Core module with its corresponding submodules.

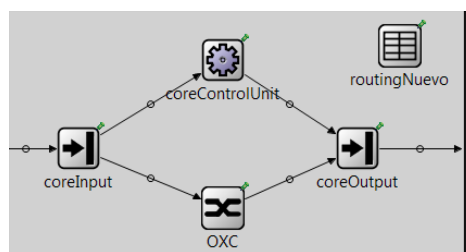

Figure 2. Core Node Submodules.

The Control Unit (CoreControlUnit) is responsible for the BCP treatment. Inside of it, the Logic Control submodule (ControlLogic) is set, which is in charge of routing, updating BCP information and generate wavelength requests. Optical–electrical (OE) and electrical-optical (EO) conversion submodules add a delay to the burst control packet.

The GatesHorizon Module contains information about the available wavelengths in order to assign one of them into the burst.

Figure 3 shows the components of the CoreControlUnit Module.

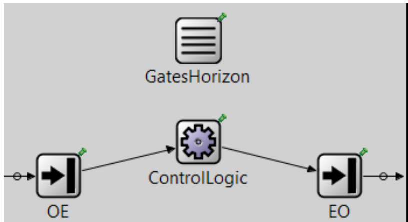

Figure 3. CoreControlUnit module.

Central and Edge nodes join together, creating the resulting OBS/WDM node as shown in Figure 4. This node is copied several times to form the evaluated network.

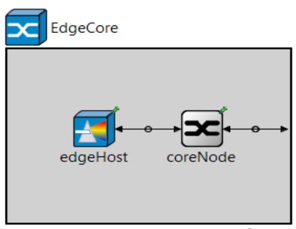

Figure 4. OBS/WDM Node.

To apply the OBS/WDM characteristics, we use The National Science Foundation Network (NSFNet), composed of fourteen nodes and twenty bidirectional connections as shown in Figure 5.

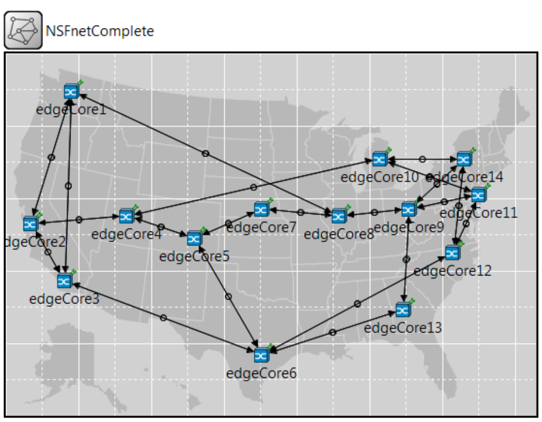

Figure 5. NSFNet.

NSFNet is a Wide Area Network (WAN) covering the U.S. territory and presents the information needed for implementation in the simulation tool OMNeT++.

IV. DWRA From the Perspective of Genetic Algorithms

When talking about routing and wavelength assignment in OBS/WDM networks, the genetic algorithm process begins with a particular number of individuals, each of them being presented as a tentative solution to the DRWA problem [15][16]. In this case, individuals refer to possible paths between the source and destination of a burst.

On the other hand, the analogy between networks and genetic processes is given by the information path, which is represented by a chromosome [17]. The latter is composed of genes, allusive to the nodes of the optical path. To provide greater clarity, the optical path is encoded using a string of integers, where each number refers to a path node, as shown in Figure 6.

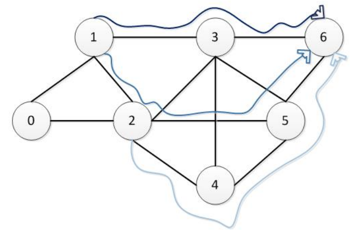

Figure 6. Coded representation of three routes. From top to bottom: {1, 3, 6}, {1, 2, 5, 6}, {2, 4, 5, 6}.

As can be seen in Figure 6, there are three chromosomes, ({1, 3, 6}, {1, 2, 5, 6}, {2, 4, 5, 6}) each one of them composed of three, four, and four genes, respectively.

V. Genetic Operators

A. *Generation of Random routes*

A set of random paths are generated with the source and destination values specified by the burst, which makes the request of a path in real time.

The function begins reaching the node from which the information is transmitted, then, it randomly chooses a node *i* whose position is adjacent to the source node; once is determined, it is marked as visited. Being in position *i*, the function performs the search and selection again to set the next node. The process is repeated several times and ends when the destination node is reached, or when all nodes adjacent to the current position have been visited, in the latter case, the function starts again.

B. *Fitness function*

The fitness function integrates information in order to reduce the blocking probability in the network. In this case, the information refers to the number of hops across the path, the distance between them and the number of fibers connected to each network node [15][18]. Now, before we continue talking about fitness function, we need to introduce an important term, i.e., the cost, which allows analyzing what network proportion is affected given a particular factor.

To assess individuals with the aforementioned characteristics, two cost functions are considered:

$$C1 = s + \alpha \sum_{i=1}^{s} (Li - Lf\, i) \tag{1}$$

C1 cost function allows to analyze the impact created by the number of hops in a route and free wavelengths on it, where s is the number of hops, L is the total number of wavelengths in the path, Lf is the number of free wavelengths, and α is a design parameter which varies between 0 and 1. This function was used in the project of Vinh Tron Le et al. [19], which gives a maximum value for α that depends on the number of wavelengths across the path.

$$\alpha < \frac{1}{W-1} \tag{2}$$

The second function represents the node congestion generated by the number of links connected to it; the more connections with other nodes present, the more the congestion link will increase. Cost C2 represents the sum of all links of the nodes across the route as shown below.

$$C2 = \sum_{i=1}^{n} Ei \tag{3}$$

where *E* is the number of connections of each node across the route.

The fitness function is inversely proportional to the cost, thus, the resulting fitness functions are:

$$F1 = \frac{1}{s + \alpha \sum_{i=1}^{s}(Li - Lf\, i)} \tag{4}$$

$$F2 = \frac{1}{\sum_{i=1}^{n}(Ei)} \tag{5}$$

The second fitness function (F2) must have a restriction because if there are no intermediate nodes in the route, the sum of links is zero, which generates an infinite value for this function, i.e., an invalid individual in the search space; as the purpose is to find an optimal global solution, we appeal to a restraint method and reconstruction of that value. In the current project, if such feature generates an infinite result, it is replaced by 1, which represents the maximum value taken by the function.

Finally, two functions are employed as, in some cases, the development of *n* approximate fitness functions may be better than a single evaluation function [15].

C. Selection

This operator uses roulette wheel selection [20]. All individuals with its respective fitness value are stored in a vector, then; this method assigns to each individual a circular sector, proportional to its fitness function, as shown in Figure 7.

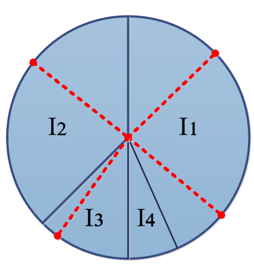

Figure 7. Roulette wheel selection.

The routes with higher fitness value will have higher probability of being selected to apply crossover operator.

D. Crossover

Once the selection process is finished, the routes are stored in vectors which are analyzed to discard those unfit (e.g., those having only two nodes), for crossover operator. Subsequently, the operator searches between the suitable paths, one common element (except source and destination nodes) to combine the routes and get the offspring, as shown in Figure 8.

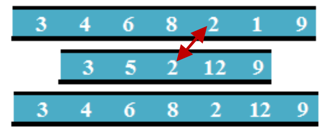

Figure 8. Crossover between two routes at node 2.

The obtained path cannot contain two equal nodes or be equal to a stored route (parents routes), if so, it is discarded, otherwise, it is saved and the fitness function is applied to each one of the children.

E. Reduction

In this process, from all resulting paths, only those with higher fitness function will be chosen. If it meets the stopping criterion, the route with the highest fitness is chosen as the solution, otherwise, the algorithm must perform more generational process until the maximum number of iterations is reached, or if a route is greater than or equal to the maximum fitness criterion.

VI. Cognitive Control Method Based on Genetic Algorithms for DRWA.

Cognitive optical networks have an architecture [12] that describes the functions performed by each layer of the network. In response to this, the control cognitive method is implemented to the Control Plane (CP) [21], since it treats directly the issues of routing, signaling, and network topology. The cognitive process is performed after the genetic algorithm had implemented in the optical network.

In order to explain the implemented cognitive method, the cognitive cycle is defined [4]. The first state corresponds to the Observation, and this refers to the network discovery. The implementation of this state allows the genetic algorithm to implement the methods and stages of its process, providing important information of the cognitive information base. Subsequently, Orientation emerges, where the information from the genetic algorithm takes significance. In this case, the factor of interest to the cognitive process is the resultant GA route, each time a burst is formed.

The third stage corresponds to the Planning cycle; this is where the information related to the best route becomes a target for cognitive control method. In other words, after obtaining the solution vector (path) in a particular network node, this is stored in a table of vectors that contain a maximum number of paths with the same origin but variable destination, which will be part of the cognitive strategy

 ISBN: 978-1-61208-315-5

implemented within the network, this cycle corresponds to Learning. The vector table size is limited and is set to design parameter. Then, and thanks to the Decision cycle, the final route vector corresponding to a node, interacts with the first stage of the genetic algorithm, "Generation of random routes."

Once inside this method, it must validate if one or more of the routes contain the same destination, (for which the request of the generation of the GA is made). If the result is positive and one or more vectors are selected, they will be part of the set of generated random routes (entering in the cognitive cycle called acting).

This method has an additional factor that adds dynamism and wide the solution space: if a new route is generated, and the vector of vectors is full, the latter discards the route corresponding to its last position and allows the entry of the new solution into the first position, displacing the other answers one box. Thus, the cognitive routes will not always be the same.

VII. Performance Evaluation of OBS/WDM Networks Based on GA with and Without Cognitive Control Methods

This section explores the parameters that affect the performance of OBS/WDM networks based on GA with and without cognitive control methods, evaluating the blocking probability and processing time.

Simulations are performed considering a dynamic traffic model where packets arrive according to independent Poisson model with arrival rate λ. The source and destination addresses of each packet are chosen randomly using a uniform distribution. The blocking probability is the first performance indicator to evaluate.

The execution times shown in the graphs are those corresponding to the OMNeT++ graphical user interface. It takes three time phases, each one of them corresponding to one, two, and three hours of real-time simulation. The tests correspond to the average value of the blocking probability and processing time, following the Maximum Likelihood Estimator method [22] with a confidence range of 85%.

Figures 9, 10, and 11 show the blocking probability for the two networks analyzed, taking maximum offset times of 72, 42, and 32 microseconds, respectively. The design parameters are:

- Mean time between packets sent: exponential (32 microseconds).
- Transmission speed: 1Gbps.
- Number of generations the algorithm: 1.
- Maximum fitness: 1.
- Size cognitive vector routes: 4
- Four wavelengths between central nodes.

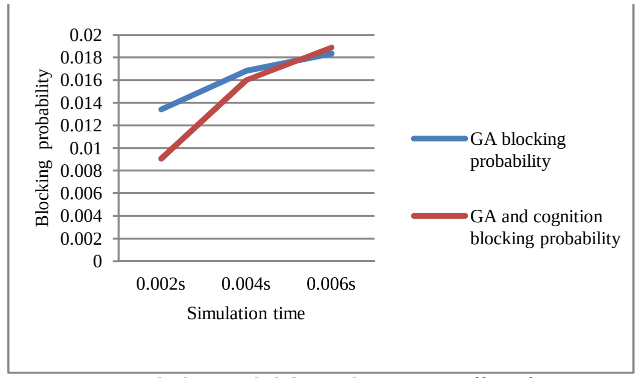

Figure 9. Blocking probability with maximum offset of 72 microseconds.

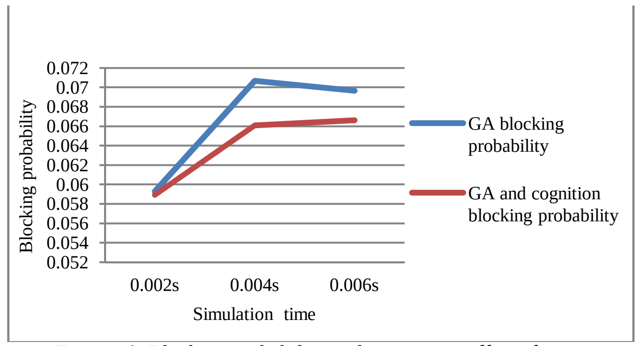

Figure 10. Blocking probability with maximum offset of 42 microseconds.

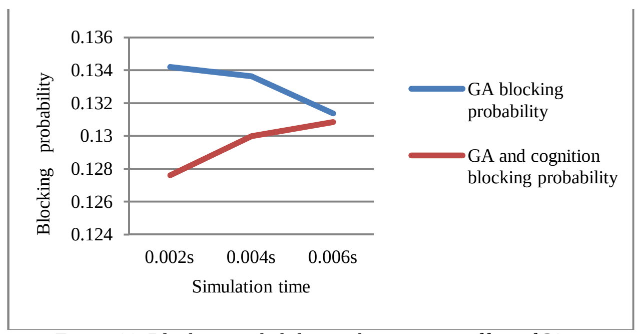

Figure 11. Blocking probability with maximum offset of 32 microseconds.

As shown in Figures 9, 10, and 11, for nine of the ten data taken, the genetic algorithm based on cognitive control performs better blocking probability values.

In Figure 12, we can see the performance of the algorithms by applying different data rates in the optical paths.

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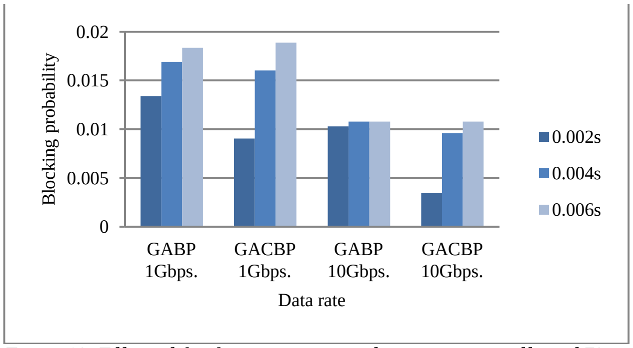

Figure 12. Effect of the data rate variation for a maximum offset of 72 microseconds.

Figure 12 shows that the genetic algorithm based on cognitive control has better response in terms of probability using 10Gbsp date rate.

Below are the results of the elapsed time for establishing the routes of a specific number of bursts, as shown in Figures 13, 14, and 15.

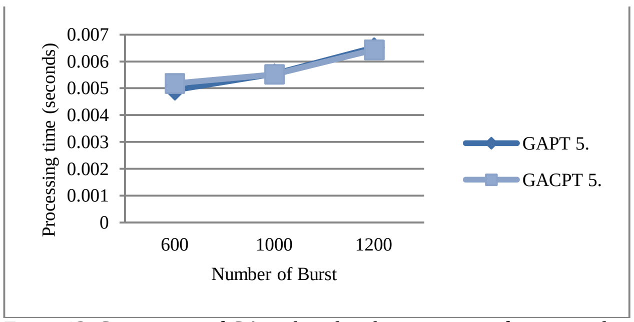

Figure 13. Comparison of GA with and without cognition for an initial population of 5 routes in the processing time estimation.

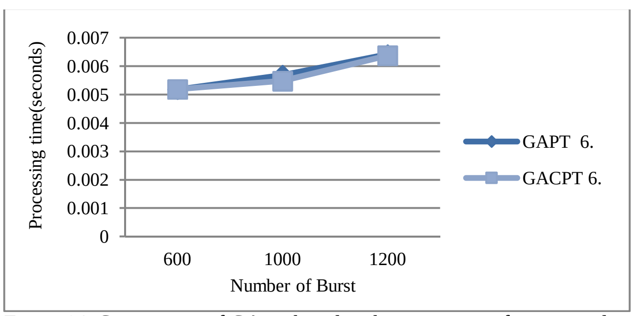

Figure 14. Comparison of GA with and without cognition for an initial population of 6 routes in the processing time estimation.

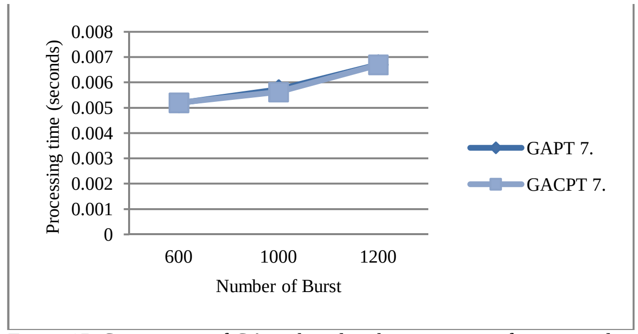

Figure 15. Comparison of GA with and without cognition for an initial population of 7 routes in the processing time estimation.

In the previous graphs, we analyzed the effect of the initial number of routes in the processing time. Although the difference does not differ significantly, we obtained better results using the genetic algorithm with the cognitive control method.

VIII. CONCLUSIONS

Among all analyzed time values and varying offset ranges, from a total of nine results, only in one case the blocking probability is lower for the network implementing genetic algorithms without cognitive control.

Using a transmission speed of 10Gbps and maximum offset 72US, the blocking probability values decrease for the genetic algorithm with cognitive control in two of the three results. Therefore, it can be inferred that in about 66% ± 15% of the cases analyzed, (using the above parameters) this heuristic method can obtain better network performance.

Conducting the evaluation of the processing time for the two designed networks it follows that in 6 of 9 results, the GA with cognitive control method has better processing time (minor), inferring that it will be in the 66.66% ± 15% of cases.

REFERENCES

[1] R. Ramaswami, K. Sivarajan, and G. Sasaki, “Optical Networks: A practical Perspective, 3rd ed., Elsevier, 30 Corporate Drive, Suite 400, Burlington, MA 01803, USA, 2010, pp. 1-30.

[2] R. Lamba and A. K. Garg, “Performance Analysis of Scheduling Algorithms In Optical Burst Switching Networks”, International Journal of Advanced Research in Computer Science and Software Engineering, vol. 1, Issue 1, Jan. 2012, pp. 62-66.

[3] X. Yu and M. Gen, Introduction to Evolutionary Algorithms, New York, Springer, 2010, pp. 3-37.

[4] CHRON (2010). “Cognitive Heterogeneous Reconfigurable Optical Network” Retrieved June, 21, 2013, from, www.ict-chron.eu.

[5] Q. Mahmoud, “Cognitive Networks, towards self aware networks,” University of Guelph: Canada, Wiley, 2007, pp. 1-19.

[6] J. Gond and A. Goel, “Performance Evaluation of Wavelength Routed Optical Network with Wavelength Conversion”, Journal of telecommunications, vol. 2, Issue 1, Apr. 2010, pp. 110-114.

[7] F. Gonzales, et al., “Lightpath routing and wavelength assignment by means of ant colony optimization”, University of Valladolid, Valladolid, Spain, February 2003.

[8] Y. S. Kavian, et al., “Genetic Algorithm for Designing DWDM Optical Networks under Demand Uncertainty”, Electrical Engineering Department, Iran University of Science and Technology, Tehran, Iran, 2009.

[9] Y. S. Kavian, “Robust DWDM Optical Networks Design using Genetic Algorithms,” Proc. First International Conference on Communications Engineering, University of Sistan and Baluchestan, Zahedan, Iran, Dec. 2010, pp. 143-146.

[10] R. Nakkeeran, A. V. Vivek, and P. Kota “Genetic algorithm based approach for routing and wavelength assignment,” Department of Electronics and Communications Engineering, Pondicherry, Engineering College Pondicherry, India, 2004.

[11] E. Kozlovski, “Survivability of Wavelength-Routed Optical Burst-Switched Networks with Guaranteed IP Services,” Department of Electronic and Electrical Engineering, University College London, Torrington Place, London, United Kingdom, 2003.

[12] L. Tomkos, et al., “Next Generation Flexible and Cognitive Heterogeneous Optical Networks - Supporting the Evolution to the Future Internet”, Future Internet Assembly, Springer, Nov. 2012, pp. 225-236.

[13] R. J. Durán, ”Advantages of Using Cognition when Solving Impairment- Aware Virtual Topology Design Problems”, University of Valladolid, Athens Information Technology, April 2011.

[14] OMNeT++ (2013). “User Manual, OMNeT++ versión 4.3”, Retrieved, June, 2, 2013, from, http://www.omnetpp.org/doc/omnetpp/manual/usman.html.

[15] U. Bhanja, S. Mahapatra, and R. Roy. “A Novel Solution to the Dynamic Routing and Wavelength Assignment Problem in Transparent Optical Networks,” International journal of Computer Networks & Comunications (IJCNC), vol.2, No.2, Mar. 2010, pp. 119-130.

[16] D. Bisbal, et al., “Dynamic Establishment of All-Optical Connections in Wavelength-Routed Optical Networks Using Genetic Algorithms”, Next Generation Optical Network Design and Modelling, Kluwer Academic Publishers, Sep. 2003, pp. 377-392.

[17] I de Miguel, R. Vallejos, A. Beghelli, and R. J. Durán, “Genetic Algorithm for Joint Routing and Dimensioning of Dynamic WDM Networks”, Journal of Optical Communications and Networking, vol. 1, Issue 7, Dec. 2009, pp. 608-621.

[18] B. Li and X. Chu, “Routing and Wavelength Assignment vs. Wavelength Converter Placement in All-Optical Networks”, University of Science and Technology Kazem Sohraby, University of Arkansas, IEEE Optical Communications, August 2003.

[19] V. T. Le, X. Jiang, S. Horiguchi, and Y. Inoguchi, “A New Fitness Function for GA-based Dynamic RWA Algorithms in Optical WDM Networks,” in Proc. of Networks, jointly held with the IEEE 7th Malaysia International Conference on Communication, 13th IEEE International Conference on, Malaysia, vol. 2, Nov. 2005, pp. 667-671.

[20] University of the Basque Country (2004), "Genetic Algorithms”, Retrieved May, 18, 2013, from http://www.sc.ehu.es/ccwbayes/docencia/mmcc/docs/temageneticos.pdf.

[21] G.S. Zervas and D. Simeonidou, “Cognitive Optical Networks: Need, Requirements and Architecture”, High-Performance Networks Group, School of CSEE, University of Essex, Colchester, United Kingdom, Jun. 2010, pp. 1-4.

[22] E. Box, J. S. Hunter, and W. G. Hunter, Statistics for Experimenters. Design, innovation and discovery, 2nd ed., Reverté S.A., 2008, pp. 17-94.