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Spectrum allocation model for cognitive wireless networks based on the artificial bee colony algorithm

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ABSTRACT

Cognitive radio through dynamic spectrum allocation allows an efficient use of the radio-electric spectrum. It is a key subject for the performance of cognitive radio networks. The purpose of the present article is to develop a spectrum allocation model for cognitive wireless networks based on the Artificial Bee Colony algorithm and assess its performance in spectrum occupancy traces obtained from monitoring the spectrum using the energy detection technique. Results show a reduction in the number of spectral handoff with no excessive execution times.

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1. INTRODUCTION

Through measurement campaigns of the occupancy of the radio-electric spectrum in countries of the European Union and the United States, recent research has shown that although there is a relative scarcity of available frequency bands, spectral occupancy ranges from 15 to 85% of its capacity thus revealing an inefficient use of this valuable resource [1, 2]. According to the previous statement, it is required to develop strategies to use the spectrum more efficiently, especially during timeframes where most users are communicating between each other. It is noteworthy to mention that some entities have started to regulate the levels of spectral occupancy, such as the FCC (federal communications commission), seeking to maintain high quality standards and satisfaction in the communication service [3-5].

Cognitive radio networks are born from scarce spectral opportunities or available frequency channels, in some bands of the radio-electric spectrum in terms of time and space. This situation drives the need to change the current communications approach and choose a more flexible one that takes advantage of the spectral opportunities in frequency bands with low levels of spectral occupancy [4, 6, 7]. However, said opportunities are not fixed within a given timeframe. In cognitive radio, two types of users develop an interaction: primary and secondary users. Primary or licensed users (PU) are direct customers of the communication service, while secondary users (SU) have the capacity to opportunistically use the frequency band that the primary user is not occupying [6, 8, 9]. This must satisfy the requirement that when a PU requires the spectral resource to communicate, the SU must abandon the channel under use and seek a new one to keep communication. This change of channel is known as spectral handoff [10-13].

The term cognitive radio first appeared in 1999, when Joseph Mitola introduced it as a part of his doctoral thesis. It was accepted by the community until became a line of research in which numerous proposals have been developed in terms of research. Furthermore, the first architectures and realistic models have been tested over the last few years to determine its viability. According to [14], "cognitive radio is a form of wireless communication in which a smart transmitter can detect the communication channels that are being used and the available ones, and instantly switch between them. This optimizes the use of the radio-electric spectrum and reduces the interference between users to a minimum".

The present article considers necessary to develop a method to simulate a cognitive radio network. Taking the previously quoted definition, the main features that the method should entail are established. It should actively seek the best solution based on predetermined criteria while also progressively improving. Therefore, the application of a swarm-based intelligence algorithm is considered.

This technique is based on the behavior of living beings of the same species that cooperate with a certain pattern to achieve a common goal such as looking for food, stability or adaptability [7, 15, 16]. This type of artificial intelligence is easy to apply and has decent computational performance when applied to distributed problems. There are several swarm intelligence methods such as ant colony algorithms, swarm particle optimization, artificial bee colony and bacterial foraging optimization. The present research consists on developing a spectrum allocation model for wireless networks based on the artificial bee colony algorithm.

2. RELATED WORKS

This section discusses the most relevant publications that served as a base for the development and conception of the present research. The authors [17] describe the relevant topics of cognitive radio and especially of spectral mobility. The parameters and factors that intervene in spectral handoff are analyzed and considered for the development of any algorithm for spectral decision such as causes, requirements, impact, classification, types of approach, control criteria and assessment criteria. Said information was considered to develop the proposed algorithm in the present article.

In [18], a multi-criteria hybrid algorithm is presented for spectrum allocation in cognitive radio networks based on analytical hierarchical process (AHP) and multi-criteria optimization and compromise solution (VIKOR). Their performance is compared with the grey relational algorithm (GRA) and random spectrum allocation. The assessment metrics used were the accumulated number of total handoffs, the average bandwidth, the average accumulative delay and the accumulative average throughput. Its operation is based on the AHP to determine the hierarchy of different assessment criteria, as well as finding the weight of each setting. Afterwards, the VIKOR algorithm decides which opportunities are most suitable.

In [19], the development and testing of an experimental cognitive radio network is described, comprised of (1) a cognitive controller that collects and processes the obtained data, which is a computer, and (2) two cognitive routers that simulate the function of secondary users. One router plays the role of a master connected directly to the cognitive controller and to the spectral detection stage, which is carried out through a software-defined radio (SDR). The other router acts as a slave while (3) a primary user is simulated by another SDR. The article also presents the applied algorithm for the detection and allocation of the experimental network. The obtained results were satisfactory in the sense that the communication of the SU was maintained in the presence of a PU with a reduction in performance as expected.

3. RESEARCH METHOD

The development of the following research takes the spectral occupancy data as a starting point, based on monitoring. This allows measuring the performance of the proposed algorithm for two levels of occupation (high and low). To design the algorithm, the ABC (artificial bee colony) algorithm is adapted with same search mechanism of possible solutions while the results can differ. In this case, the results correspond to various GSM frequency bands that are available to establish communication. After defining the channels, they are assessed with another section of the measured spectral occupancy data.

3.1. Measuring Equipment

To develop the present research, the following resources were used:

a. A spectrum monitoring system described in Table 1, to carry out the capture process of the spectral occupancy data in the GSM band, which includes the spectrum analyzer MS2721B Anritsu.
b. Multiple electronic databases to consult and build literary review for CRN.
c. Matlab software used to develop the simulator and the proposed ABC algorithm.

Table 1. Specifications of spectrum monitoring equipment

Equipment	Specifications	
	Frequency range	Reference
Discone Antenna	25 MHz – 6 GHz	Super-M Ultra Base
Bandwidth cable	DC – 18 GHz	CBL-6FT SMNM+
Low-noise amplifier	20 MHz – 8 GHz	ZX60-8008E-S+
Spectrum analyzer	9 kHz – 7.1 GHz	MS2721B Anritsu

3.2. Spectral Occupancy Data

The captured data were used to assess the performance of the proposed algorithm. The data capture process involved an energy detection technique that contributed to build a power matrix. Afterwards, the probability of false alarm was defined as well as the decision threshold to determine the occupancy or availability of each monitored channel, in order to define the availability matrix [20, 21]. After a statistical analysis of the availability matrix, two traces of spectral occupancy with high and low levels of occupation, respectively which were split into 50% for algorithm training and 50% for assessment [22].

3.3. Proposed ABC Algorithm

An algorithm is required that is versatile enough to adapt to the changes of spectral occupancy according to the transmission time, with the capacity to assess the best frequency bands so that a SU can establish communication. Based on the previous statement, the ABC algorithm based on swarm intelligence is applied by establishing an analogy to the food search process of a group of bees, where the possible solutions are represented by the found food sources.

In general, there are three groups of bees in the ABC algorithm: employees, scouts and observers. The employees exploit the food sources (possible solutions) initially found by a group of scout bees. A single employee bee is located in each food source, so that the number of employee bees is equal to the number of solutions to be found [23-25]. After handling the first food sources, a search and selection process is carried out by the employee and observer bees, which is different depending on which type of bee performs the action. In any case, the purpose is to find better food sources to take advantage of them. To give more clarity, the steps of the ABC algorithm are described. Initially, the main parameters must be defined to apply the algorithm:

a. The size of the bee population SN
b. The number of MCN cycles to carry out during the search for food
c. The maximum value x_max and the minimum value x_min that cover the solution.
d. The limit number of attempts to improve a food source L

The first phase of the algorithm consists on initializing the food sources or solutions using (1), in order to find random values within the defined range that correspond to the initial targets of the employee bees:

$$x_i = x_{min} + rand(0,1)(x_{max} - x_{min}) \quad (1)$$
$$Con\ i \in [1,2,3,4 \dots SN]$$

When the employee bees are positioned in the initial solutions x_i, new neighboring solutions v_i are randomly sought through (2), where x_i denotes the current position, x_k denotes the position of another food source, and $\emptyset_i$ denotes the random value between -1 and 1. After performing the search, a comparison is established between each v_i and x_i in order to know and remain in the same food source.

$$v_i = x_i + \emptyset_i(x_i - x_k) \quad (2)$$
$$with\ i \neq k$$

Then, the scout bees carry out a search process to determine a measuring parameter to quantify how suitable is x_i. This parameter is known as fitness and is determined for each solution of the employee bees. The method to determine this variable depends on the problem to be solved, whether a function should be minimized or maximized. In general, the fitness of the food sources is related with the assessment of the target function with the values of x_i as seen in (3). The probability P_i of choosing the solution x_i for each fitness value using (4) is crucial to decide which x_k is visited by the observer bee. When the value of x_k is obtained, (2) is used once again and the best solution is chosen between v_i and x_i.

$$fit_i \rightarrow f(x_i) \quad (3)$$

$$P_i = \frac{fit_i}{\sum_{n=1}^{SN} fit_n} \tag{4}$$

Finally, the process is repeated by the scout bees starting from the search process up to finding an acceptable solution or meeting the number of MCN cycles. If a food source does not improve after L cycles, it will be abandoned and replaced by a new random source x_i of (1).

3.4. Adaptation of the ABC Algorithm

The described ABC algorithm can be adapted to the requirements of searching tasks in the best frequency bands that are available for communication, as follows:

The results obtained from measurements are conditioned in two matrices in which the variation between columns corresponds to different frequency bands and the variation between rows corresponds to the increase in the timeframe of measuring the spectrum occupancy. The first matrix is used to train the proposed method and the second matrix is used to assess it.

During the training phase, the goal is to build a path that connects the start and the end of the training matrix using the available frequency bands of the radio-electric spectrum (channels), in which the secondary user (SU) establishes communication. To build said path, the first section of the algorithm seeks time "brackets" x_i using (5) and (6), in which a frequency band is available to establish communication, then new "brackets" v_i are generated using (2) and a comparison is established between x_i and v_i to select and save the channel with highest availability time.

$$Coordinate\ x_r = x_{r\_min} + rand(0,1)\left(x_{r\_max} - x_{r\_min}\right) \tag{5}$$

$$Coordinate\ x_c = x_{c\_min} + rand(0,1)\left(x_{c\_max} - x_{c\_min}\right) \tag{6}$$
$$x_i = stretch\ contained\ in\ (x_r, x_c)$$

Within the first group of brackets found, the bracket with the highest availability time is chosen and defined as the initial bracket of the solution path. When the initial bracket is defined, the algorithm seeks new brackets x_i and v_i that can connect with the original path and extend it. To define which brackets x_i are chosen for the extension of the solution channel, to those channels that have the best availability times and meet the requirement of remaining within the range of the solution path. Said channels are assigned a fitness function and a probability P_i using (7) and (8). Based on the previous results, a bracket is chosen to be included before or after the current solution, depending on its location. The current setting of the built channel is stored in order to repeat the cycle from the beginning, with new values of brackets x_i.

$$fit_i \rightarrow availability\ time\ (x_i) \tag{7}$$

$$P_i = \frac{fit_i}{\sum_{n=1}^{SN} fit_n} \tag{8}$$

It is required to build several paths in order to have various options of frequency bands for all times. These paths may be needed in the assessment stage in case a PU asks for a channel where a SU is transmitting. Before launching the algorithm, the number of desired paths is introduced as an input. When the number of channels is determined, the algorithm moves on to the assessment stage.

During the assessment stage, the communication is established through the channels found during the training stage. When the chosen channel is busy, communication is established through the following option found in the previous stage. A jump (handoff) is carried out between frequency bands and, if the new one is also occupied, then the next one is chosen. This process is repeated during the total time allocated in the assessment matrix. If needed, all channels found in the previous stage are assessed until one of them is available. In contrast, if no frequency band is available to transmit, the algorithm stops and recommends to restart the process by increasing the number of solution channels to be obtained during the training phase. Hence, the total number of handoffs and failed handoffs that a cognitive radio secondary user should perform are simulated during the assessment time of the algorithm.

Pseudo-code

The pseudo-code of the proposed model is described:

Input data: Population, Channels, t_eval, Matrix_train, Matrix_eval

```
% Start algorithm
% Start training stage
for z = 1:Channels
        while ok == 0
                for i = 1: Population
                        x_r = rand(0,1)*(length(Matrix_train)); % Equation (5)
                        x_c = rand(0,1)*(length(Matrix_train)); % Equation (6)
                        x_i = (x_r, x_c);
                        L_xi = length_stretch(xi); % Length stretch associate to xi
                end
                for i = 1: Population
                        v_i = x_i + phi*(x_i – x_k);
                        L_vi = length_stretch(vi); % Length stretch associate to vi
                        if L_vi > L_xi
                                x_i = v_i;
                        else
                        end
                end

                % Verify if xi belongs to Channel_z
                If L_xi(1) < Channel_z(1) && L_xi(end) > Channel_z(1) || L_xi(1) > Channel_z(1) &&
        L_xi(end) > Channel_z(end)
                        x_ok = xi;
                else
                end

                fit_i = length_stretch(x_ok); % Length stretch associate to x_ok, eq. (7)
                P_i = fit_i/(sum(fit_i)); % Equation (8)
                x_select = rand(x_ok); % Selection depends to P_i
                Channel_z = [Channel_z; x_select];
                If Channel_z(1) = 1 && Channel_z(end) == 1
                        ok = 1;
                else
                end
        end
end
% End training stage
% Start evaluation stage
Channel_act = Channel_1
for i = 1:length(Matrix_eval)
        if Matrix_eval(Channel_act(i)) == available
                Result(i) = 1;
        else
                while ok_eval = 0
                        Channel_act = Channel_act + 1;
                        if Matrix_eval(Channel_act(i)) == available
                                Result(i) = 1;
                                Channel_act = Channel_1;
                                ok_eval = 1;
                        else
                        end
                end
        end
        ok_eval = 0;
end

% End evaluation stage
% End algorithm
```

3.5. Assessment metrics

To assess the proposed algorithm, the number of total handoffs and failed handoffs for different values of the artificial bee population and execution time of each simulation with the purpose of finding a balance between the three variables: handoffs, processing time and population, that render the method viable for possible applications in the nearby future.

4. RESULTS AND ANALYSIS

The results of spectral handoffs are presented with the proposed method for two traffic levels (high and low) and for populations of 100, 200, 300, 400 and 500 as shown in Figure 1-5 respectively. In Table 2, the average results are summarized for 5 executions in each population. The number of channels found during the training phase was 6 in all cases.

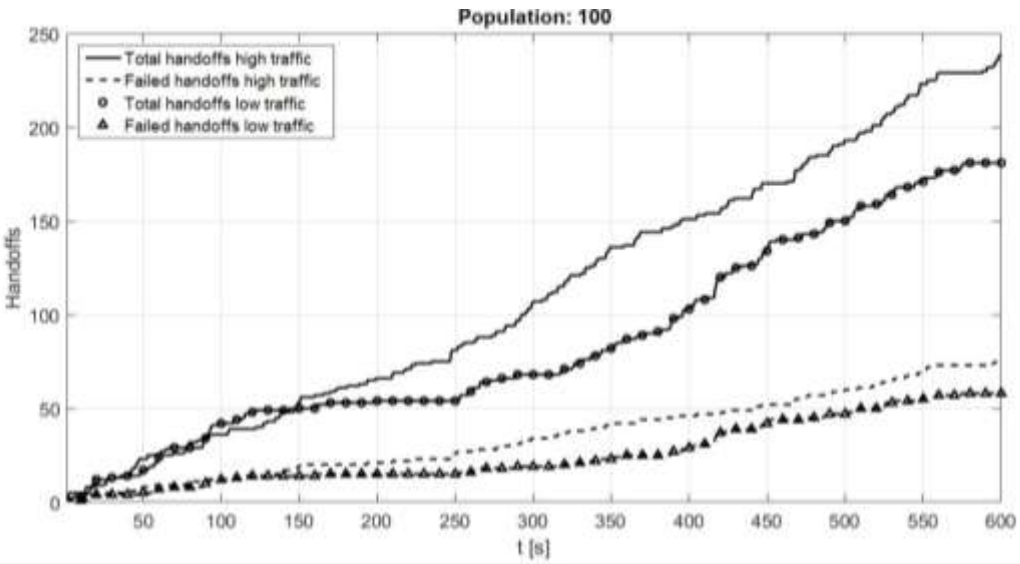

Figure 1. Results with the proposed method for 100 bees

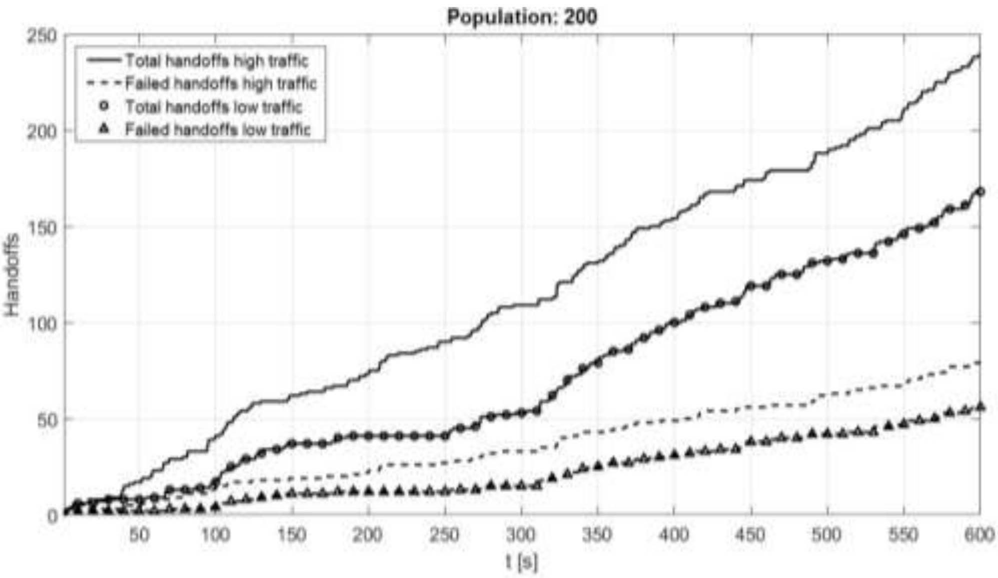

Figure 2. Results with the proposed method for 200 bees

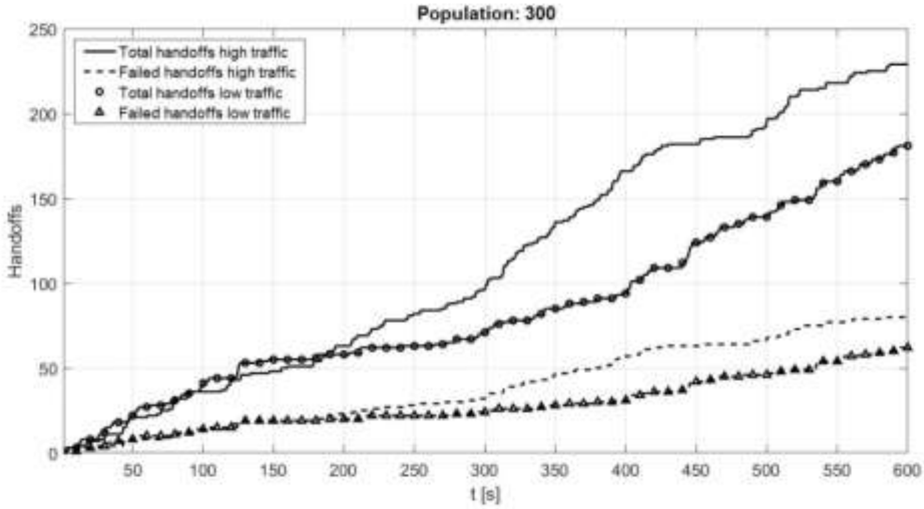

Figure 3. Results with the proposed method for 300 bees

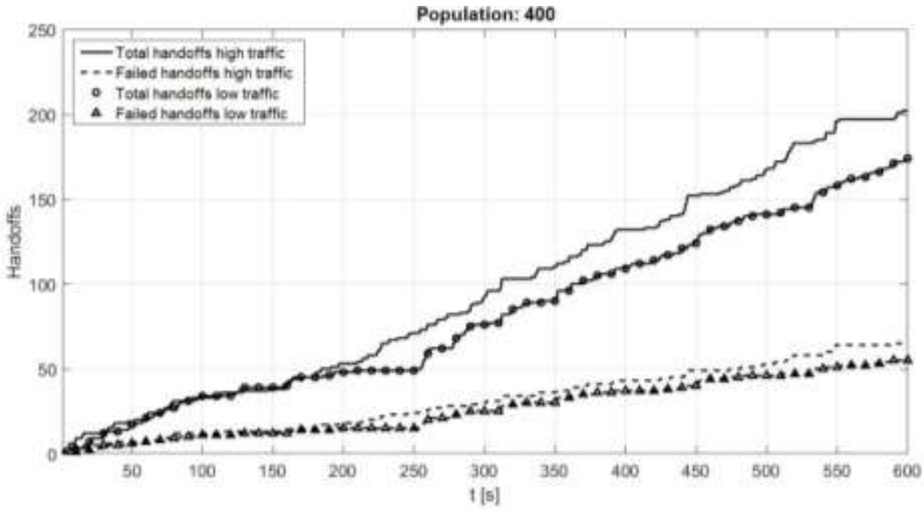

Figure 4. Results with the proposed method for 400 bees

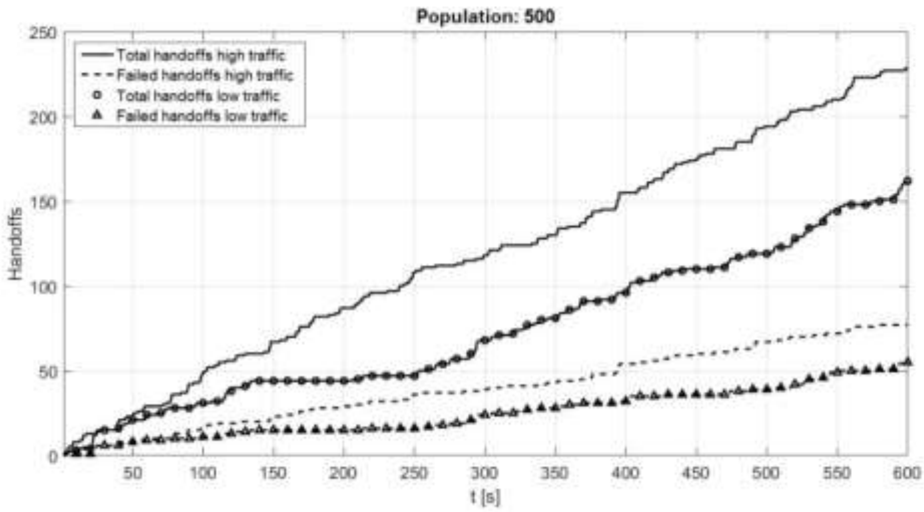

Figure 5. Results with the proposed method for 500 bees

The summarized average of the results for five executions of each population is shown in Table 2. The control parameters of the algorithm are the size of population and the number of channels to be found. These are adjusted depending on the assessment time and the frequency range of the spectrum in which the simulation is carried out. These affect the robustness of the algorithm as well as the execution time. However, the approach should be cautious in terms of defining the values of both parameters, since the non-convergence of the algorithm can take place if either one of them is chosen incorrectly. As expected, less handoffs take place when spectral occupancy is lower since there are higher availability times within the frequency bands, as seen in Table 2. The assessment of the algorithm with high traffic requires up to 238 total handoffs, while the assessment with low traffic leads to 180 total handoffs.

Table 2. Average summary of the obtained results

Population	High traffic		Low traffic		Execution time [s]
	Total handoffs	Failed handoffs	Total handoffs	Failed handoffs	
100	236	81	178	58	171
200	238	86	180	61	127
300	238	88	170	56	105
400	228	76	161	52	106
500	224	76	163	57	117

Furthermore, the simulations for different populations and the same level of traffic, the number of handoffs behaves similarly in all cases. Table 2 shows that the assessment of the algorithm with high traffic has between 224 and 238 handoffs while the assessment with low traffic shows between 161 and 180 which are limited intervals. The assessment phase always receives the same number of solution channels and the size of the population is independent from said value. Hence, the network behaves similarly in this aspect.

However, the variation of the number of handoffs for each population can be determined to then conclude which algorithm shows better performance. Table 3 is used to compare the handoffs of the same category. Finally, the average participation of all types of handoffs is obtained. Higher values indicate a higher number of handoffs and lower performance. Therefore, a metric can be established to assess different populations considering the number of handoffs as a criterion. In this case, the simulations with a population of 400 bees showed better performance with a total participation of 89.2%, followed by the results for populations of 500, 100 and 300 with a respective participation of 90.8%, 96.2% and 96.8%. The population with the lowest performance for this criterion was comprised of 200 artificial bees with a total participation of 99.3%.

Table 3. Participation percentage of the number of handoffs compared to the maximum value in each category

Population	High traffic		Low traffic		Participation
	Total handoffs	Failed handoffs	Total handoffs	Failed handoffs	
100	99.2%	92.3%	98.9%	94.4%	96.2%
200	99.7%	97.7%	100.0%	100.0%	99.3%
300	100.0%	100.0%	94.9%	92.2%	96.8%
400	95.6%	86.6%	89.5%	85.0%	89.2%
500	93.8%	85.9%	90.9%	92.5%	90.8%

It is also proposed to use the execution time as an assessment criterion where the participation value is shown in Table 4 as a percentage of the execution time (10 minutes) for the results in each population level. Similarly, to the analysis carried out in the previous paragraph, higher participation values mean higher execution time and lower performance. Hence, the population with the lowest performance has 300 bees with a participation of 17.4% followed by the populations of 400, 500 and 200 with participations of 17.4%, 19.5% and 21.2% respectively. The population with the lowest performance according to this criterion had 100 bees with a participation of 28.6%.

Table 4. Participation percentage of the execution time for each population

Population	Execution time [s]	Assessment time [s]	% Participation
100	171.5	600	28.6%
200	127.3	600	21.2%
300	104.6	600	17.4%
400	106.3	600	17.7%
500	117.3	600	19.5%

5. CONCLUSION

There is a reduction in the execution time of the algorithm as the population grows larger. According to Table 4, the highest execution time was 171 seconds for a population of 100 artificial bees and said time was increasingly smaller for populations with 200 and 300 bees yet it stabilized for 400 bees. Their respective times were 127, 104 and 106 seconds. This trend is a consequence of a deeper search process and a subsequent higher number of options of available brackets for transmission. Hence, the algorithm has a more effective selection process and thus improves the performance of said parameter keeping in mind that each bee represents a bracket found in the training phase. In terms of the population parameter, its growth offers more options of available brackets in the training phase and boosts the execution time since it finds solution paths more easily. Nonetheless, it is paramount to carefully choose the value of this parameter since it is intimately tied to the size of testing matrix. If the population is large and the matrices are small, the brackets cannot be found in the first training phase and the algorithm does not converge. If the population is small and the matrix is large, the algorithm takes too long to find solution paths which is also unacceptable. Finally, the population that outperformed the others was the 400-bee population since it has the lowest number of handoffs (participation of 89.2%) and the second lowest execution time (106 seconds with a participation of 17.7%) according to Table 2-4. Therefore, it can be concluded that, for the developed algorithm, a population size can be determined that offers the best performance without the need to have the highest value among a set of alternatives.

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