Minimizing Interference In Frequency Assignment Problem Based On Guided Particle Swarm Optimization Algorithm

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Abstract: This paper presents a modified approach based on Particle Swarm Optimization algorithm (PSO) for minimizing interference in Frequency Assignment Problem (FAP). This problem, known to be NP-hard, is to find an assignment of limited available frequencies for a number of communication cells. The main goal of the minimum interference FAP (MI-FAP) is to minimize the interference penalty cost provided in the solution. This cost related to the number of violated interference constraints, which predefined in interference matrix (IM). The modified algorithm named Guided search PSO (GPSO), which improve the particle location update strategy of the regular PSO to escape from local minimum. The proposed algorithm, enhance the convergence rate; robustness of the regular algorithm, and optimization stability of the search results. The computational efficiency and quality of the solutions obtained from the presented algorithm has been tested on well-known benchmark problems. The results obtained shows more efficiency than other results of previously related works.

Index Terms: Communication cells; Convergence rate; Frequency Assignment problem; Interference; Local minimum; Particle swarm optimization

1. INTRODUCTION

In communication systems network, the available spectrum bandwidth is limited in scope, with the incredible increasing number of the user. In this case the concept of frequency reuse is not uncommon, and as a result the operating cost increased due to the interference incurred between the communication system cells. It is important to improve spectrum utilization through planning reasonably, and effectively the available frequencies. The process of exploiting the available frequency resources to meet system capacity named Frequency Assignment Problem (FAP). The FAP belongs to the NP complete combinatorial optimization problem that arisen by Metzger 1970 [1]. The limited frequency resources must have reused precisely, because it has both adjacent, and co-channel interference. Informally, given a communication system network, FAP aims to assign a set of available frequencies to each cell of the network such that the total interference level of the frequency assignment is minimized. There are three categories into which FAP is classified, Fixed Frequency Assignment (FFA), Dynamic Frequency Assignment (DFA) and Hybrid Frequency Assignment (HFA) for more details in [2]. Generally, FAP can be described within a communication system N consists of a set of nodes *n*i, and a limited predefined set of frequencies called bandwidth, denoted by B. For every node $n_i \in N$ a subset $Dn_i \subseteq B$ of available frequencies is specified, which referred to the domain of the node. This domain represents a subset of $m(n_i)$ frequencies must be assigned to *n*i.

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This subset ($m(n_i)$) introduce the first type of constraints in the FAP models known as multiplicity constraints, which represents the required number of frequencies for every cell in the communication system and define as:

$$\sum_{f \in Dn_i} x_{fn_i} = m(n_i) \quad \forall\, n_i \in N \qquad (1)$$

For every cell n_i and the available frequency *f* where, $f \in Dn_i$ we define

$$x_{fn_i} = \begin{cases} 1 & \text{if frequency } f \in Dn_i \text{ is assigned to vertex } n_i \in N \\ 0 & otherwise \end{cases}$$

where,
$m(n_i)$: The number of frequencies required to cell n_i,
Dn_i: The domain of cell *n*i, $Dn_i \subseteq B$.
As mentioned, the communication system may have several interferences between different pairs of nodes as a result of frequency reuse. The system interference may happen when the difference of assigning certain frequencies for pair of nodes is less than certain predefined value. The interference level between pair of nodes is another cause to increase the service blocking probability of the system if it exceeds the maximum predefined threshold. The interference / packing constraints are the second type of FAP constraints, which defined as following:

$$x_{fn_i} + x_{gn_j} \le 1 \quad \forall n_i n_j \in E, f \in Dn_i, g \in Dn_j \;, i \ne j: \quad (2)$$
$$|f - g| \ge R_{n_i n_j}$$

$|f - g|$: Actual allowable difference between frequency *f*, and *g* assigned to node *i,* and *j* respectively without any interference.
$R_{n_i n_j}$: Minimum allowable difference between frequency *f*, and *g* assigned to node *i,* and *j* respectively without any interference. The use of the spectrum efficiently becomes one of the most important aspects for evaluating new communication systems design [3]. It is obvious that the probability of blocking the service increase as a result of the development in the communication system, which

extremely limited by the capacity constraints of the available frequency spectrum. This is due to the high level of interference that incurred between pairs of cells, so proper utilization of frequency assignment techniques becomes essential in solving the MI-FAP. This paper proposes a modified algorithm named GPSO, based on particle swarm optimization algorithm for tackling the MI-FAP. The paper is organized as follows: section 2 expose the problem formulation, where in Section 3 related works are introduced. A brief introduction for regular PSO in section 4. This is followed by section 5, which introduce the proposed algorithm, the solution structure, flowchart, and finally an illustration of different steps for the algorithm stages. Benchmark instances are shown in section 6. Extensive computational results and other related works are exposed in section 7. Finally, conclusion is reported in section 8.

2. The MI –FAP Model

The quality of the frequency plan in a communication system is one of the key factors for evaluating the provided service. This quality may be degraded as a result of the inaccurate Interference Matrix (IM), which estimates the level of interaction between any two nodes in the communication system. There are several quality indicators for the service delivered by the system in [25] for more details. One of the most important ones is a number of value of a cost function in an assignment algorithm, which depends on the IM. The physical quantity behind the cost that the elements of the IM represent varies. The FAP has several physical quantities values may introduce for example intermodulation interference, hand over rate between two nodes, adjacent channel interference, co channel interference, and many other types found in [4] for more details. This paper only two types of physical quantities are exposed, which are the adjacent, and co-channel interference constraints. The objective in this model is to Optimize the operating cost of the system through minimizing the costs result from violations of the interference constraints. In other words, different cells may satisfy the multiplicity constraints (equation 1) despite of not satisfying the packing constraints (equation 2). The mathematical formulation for the MI- FAP model illustrated as follows:

$$\min \sum_{n_i} \sum_{n_j \in E} \sum_{f \in D_{n_i}} \sum_{g \in D_{n_j}} p_{fgn_in_j} \quad x_{fn_i} x_{gn_j} \tag{3}$$

$$S.to \quad \sum_{f \in Dn_i} x_{fn_i} = m(n_i) \qquad \forall n_i \in N \tag{4}$$

$$x_{fn_i} + x_{gn_j} \leq 1 \; \forall n_i, n_j \in E, f \in Dn_i, g \in Dn_j \; , i \neq j: \tag{5}$$

$$|f - g| \geq R_{n_in_j}$$

$$x_{fn_i} \in \{0,1\} \; \forall ni \in N, f \in Dn_i \tag{6}$$

$$m(n_i) \in \mathbb{Z}_+ \quad \forall ni \in N \tag{7}$$

This model introduces a variable $p_{fgn_in_j}$, that represents considered penalty cost in case of violating the interference constraint in case of assigning frequency *f*, and frequency *g* for nodes n_i, n_j and $i \neq j$. The interference constraints in communication system is described by an $N \times N$ symmetric matrix. This matrix is a matrix whose elements give the separation that should exist between the channels corresponding to the cell row and the cell column. According to this separation a penalty cost is estimated in case of that any of the separation constraint between nodes violated. When assigning frequencies, the cost function steers towards such an assignment that minimizes that physical quantity in the network that the IM elements represent.

3. Related works

The MI-FAP has many applications in different fields such as Duque- Anton et al. (1993), Beckmann et al. (1999), Luna et al. (2007), and Del Ser et al. (2012), for Cellular Mobile and Telecommunication Networks applications; Military applications for more details in [6], also Radio and television [3], and finally Satellite communication in [7, 8] for more interest. Various approaches and methods have been proposed to tackle the MI-FAP. For example, we can find Tabu search and path relinking in [9, 10, 11, 12], Ant Colony optimization algorithms and evolutionary approaches in [13], simulated annealing algorithms [15], Genetic algorithm [3], a Branch and cut algorithm [16], a Cultural algorithm [17], hybrid approaches [8, 18, 19] and hyperheuristics [20], and others methods like [5, 21, 22, 23, 24].

4. Classical PSO Algorithm

PSO algorithm, which introduced by Kennedy and Eberhart [26] is inspired by the social behavior of bird flocking or fish schooling. In PSO individuals called particles, which iteratively explore the search space, and trying to provide a candidate solution near the optimal solution for the problem with regard to a given measure of quality. Interaction among individuals refines the experiential knowledge about the environment, and enhances the progress of the swarm toward optimality. In PSO, a set of particles (*N*) of swarm is defined. Each particle represents a potential solution in the solution space and is characterized by its position and velocity. Each particle updates its position and velocity based on its own best position (*p*best) as well as the best position of the entire swarm (*g*best). For a D dimensional problem with N particles the position vector is represented as $X(t) = (X_1(t), X_2(t), X_3(t), \cdots X_N(t))$ where, $X_i = (x_{i1}, x_{i2}, x_{i3}, \ldots x_{iD})$ and the velocity vector is represented as $V(t) = (V_1(t), V_2(t), V_3(t), .., V_N(t))$ where $V_i = (v_{i1}, v_{i2}, v_{i3}, \ldots, v_{iD})$, where, $i = 1$ to N, and t is the iteration number . In classical PSO algorithm the position and velocity for each particle in the swarm initialized to independent random values. The second step is to calculate the preferred objective function of each particle based on their positions, then each particle 's current fitness value is compared with previous *p*best value. If the current value is better than the previous value, then set the *p*best value to the current value and fix *g*best of the swarm as best of all *p*best. The velocity and position of each particle in the swarm are updated according to the following two equations

$$V_{i,d}^{t+1} = wV_{i,d}^{t} + C_1 * R_1 * (pbest_{i,d}^{t} - X_{i,d}^{t}) + C_2 * R_2 * (gbest_{i,d}^{t} - X_{i,d}^{t}) \tag{8}$$

$$X_{i,d}^{t+1} = X_{i,d}^{t} + V_{i,d}^{t+1} \quad (9)$$

Where, C_1, C_2 are two constant multiplier terms known as "self-confidence" and "swarm confidence" which respectively provide the influence of the *p*best, and *g*best on the velocity update formula. R_1, R_2 are independent random numbers uniformly distributed in the range [0, 1]. *w* is the inertia weight. $V_{i,d}^{t}$, $X_{i,d}^{t}$, and $Pbest_{i,d}^{t}$ are the velocity, position and the personal best of i^{th} particle in d^{th} dimension for the t^{th} iteration respectively. The $gbest_{i,d}^{t}$ is the d^{th} dimension of best particle in the swarm for the t^{th} iteration.

5. GPSO Algorithm

The implementation simplicity represented mostly in The particle movement updating, scalability in dimension, and good empirical performance as a result are considered the main desirable properties of the regular PSO. The process of searching for the most optimal solution has many disadvantages such as the random initialization of the particles velocity and positions. This may guide the particles away from the optimal solution in the consequent iterations. Also, fast convergence rate result in being trapped to a good local optimum. This is due to the particles converges to the global best position discovered during the algorithm execution, which means that the particles converge to points that lie between their *p*best and the *g*best discovered by all particles in the swarm. Moreover, the particle behavior does not guarantee convergence to a global best solution, or even a local solution, only to a best position found. This is due to that when a particle present position *X*i in the swarm equal to both its previous best *p*best, and global best position *g*best in the swarm its velocity will approaches zero, resulting in all particles will stop moving. The aforementioned back draws in the regular PSO algorithm are considered the real motivation for introducing the modified algorithm GPSO.

5.1 GPSO solution structure

This work explores an alternative for improving the PSO for tackling MI-FAP. The execution code of the provided algorithm based on Labview programming. The structure of the provided solution for each particle in the swarm is a string contains integer numbers that represents the indices of the candidate frequency from the predefined domain *D* for each cell n_i in the network *N*. The structure length delivered for every particle is the sum of all numbers of frequencies required for all nodes in the network. This structure is divided into labeled slots *Q*=1,…*X* each group of slots represents the required number of frequencies for ni in order sequence. Figure (1) illustrate the delivered structure as an example of a communication network system *N* consists of three cells *n*i, i=1,2,3 for simplicity. The required number of frequencies (multiplicity constraints) $m(n_1) = m(n_2) = 3$ while, $m(n_3) = 2$. This means that the structure length will be 8 = (3+3+2). The network has two domains each one consists of a defined set of five frequencies D_1 = {20, 35, 45, 55, 70}, D_2 = {20, 40, 55, 70, 80}. Suppose that n1, n2 ϵ D_1 = {20, 35, 45, 55, 70}, and n_3 ϵ D_2 = {20, 40, 55, 70, 80}. The structure of delivered candidate's indices for each particle in the swarm is exposed in figure (1.a), where the counterpart frequencies of the candidate's indices illustrated in figure 1.b.

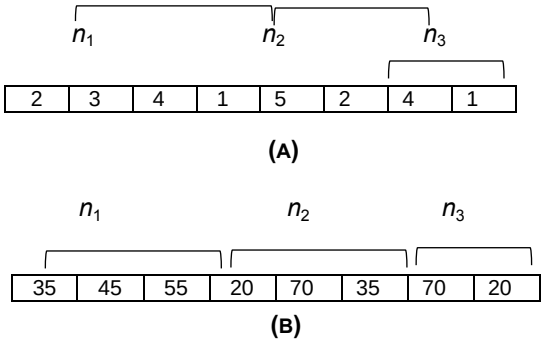

FIGURE 1. *GPSO SOLUTION STRUCTURE* ***(A)*** *CANDIDATES INDICES FOR ALL NODES* ***(B)*** *COUNTERPART FREQUENCIES*

5.2 GPSO flowchart

The implementation of the GPSO in both first stage (regular PSO), and second stages for tackling the MI-FAP as shown in figure (2) has been adapted to satisfy the FAP nature. The execution of the GPSO algorithm incurred in two stages. In first stage the regular PSO algorithm is achieved through the main three operations. The first operation is random initialization for the swarm particles then, second is the evaluation of the fitness function. Finally, modification of the swarm to provide the new particles positions.

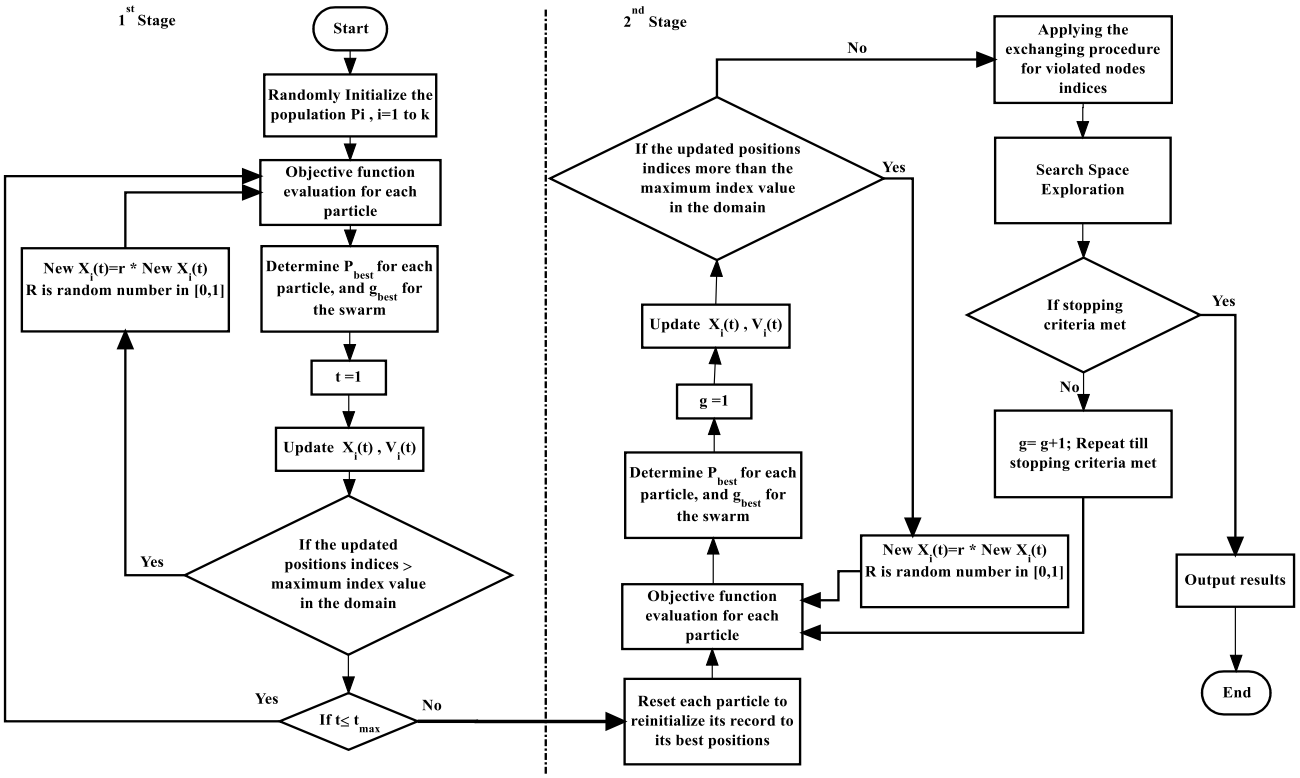

FIG.2. *GPSO GENERAL FLOWCHART*

These three operations are repeated until the stopping criterion; maximum number of iterations is reached. The execution of the provided GPSO in second stage starts from the solution delivered from the advanced regular PSO in first stage. The main idea is to give the opportunity to the particles of the swarm in the second stage to learn from the experience of their peers in the first stage, and avoiding their mistakes.

5.3 GPSO First stage

The general GPSO flowchart expose that there is a similarity in most steps between the first stage and the second stage. The first stage, which represents the regular PSO, has been modified with a furthermore step is that checking the indices violation. Also, the second stage in addition, has three main differences other than the first stage. In this subsection the first stage will be introduced briefly, and deeply in the following subsection due to the aforementioned similarity as shown in figure 2. In first stage the regular PSO also, has an alteration to satisfy the nature of MI-FAP. The decision of particles updating positions manipulation depends not only the algorithm regular modification in equation 9, but also on the particle index of the candidate indices in the specified domain for each cell. This incurred if any index of the candidate indices violated the maximum index number in the specified domain for each cell. In this case the particles position modification achieved as the following equation

$$x_{jd}^{t+1} = r * (x_{jd}^{t} + v_{jd}^{t+1}) \quad (10)$$

Pseudocode of the Algorithm first stage is presented as follows:

1. Set number of iterations *t*.
2. Set number of population size *i*, that represents the particle index P_i in the swarm.
3. Randomly select the candidates' domain index for network nodes for each particle in the swarm P_i.
4. Evaluate the solution of the nodes candidates index for each particle in the swarm according to equation 3.
5. Determine the global best gbest in the swarm, and the local best pbest for each particle of the swarm.
6. Applying the swarm manipulation according to equations 8, and 9.
7. Check the candidates index domain violation for each node for all particles.

7.1. If any of candidate's index violated apply to equation 10, and go to step 8.

7.2. If not go to step 8.

8. Repeat from 4 to 7 till reaching the stopping criteria.

The output results from this stage is considered as a seed for initialization to all particles in the second stage swarm in order to escape from local minimal.

5.4 second stage execution

In this section all different steps of the second stage other than the first stage will be illustrated. This is due to the similarity of the inherent steps between stages. As mentioned above that there are three differences between the stages of the provided algorithm. The first is the guided initialization instead of random one. Second the exchanging procedure for violated nodes indices, and finally checking constraints violation for feasibility evaluation. These difference make the introduced algorithm GPSO has to achieve a high degree of exploration, and diversity to

provide better solutions. In the second stage, each particle start initialization from its record of the best position obtained in the first stage. This is achieved with periodic resetting, based on the iteration count in the first stage. The main target of this stage is to avoid making direction and velocity decisions on the basis of random initialization, so they start searching from where their peers stopped. Pseudocode of GPSO initialization as follows:
1.Define particle population P_j, j=1,…s, with swarm size s
2.Set j=1
3.Initialize the structure of Pj $\forall n_i \in N$.
3.1. For every Pj in the swarm Set the candidates index provided from first stage for every Q $\forall n_i \in N$.
4. Return the counterpart frequency for Q =1 to X,

$$X = \sum m(n_i)$$

The objective function evaluation and manipulation preceding the initialization step are executed in two steps. First in the fitness function evaluation, the GPSO check the violated constraints according to the predefined distances between pairs of nodes, which defined in the interference matrix. Then, execute the objective function evaluation for every particle in the swarm. Pseudocode of GPSO objective function evaluation as follows:
1. For every P_j Check constraint violation for Q $\forall n_i$

$x_{fn_i} + x_{gn_j} \leq 1 \quad \forall n_i, n_j \in E, f \in Dn_i, g \in Dn_j \ , i \neq j$: $|f - g| \geq R_{n_i n_j}$

1.1. Mark violated Q in sequence till Q=X for Pj

2. For every Pj calculate the objective function according to

$$C = \sum_{n_i n_j \in E} \sum_{f \in D_{n_i}, g \in D_{n_j}} p_{fgn_i n_j} \quad x_{fn_i} x_{gn_j}$$

3. Get the min of C for all P_j in the swarm
4. Set $g$best of C is the global best

The provided algorithm does not return the updated particles positions until checking if the frequency index of the candidate solution within the maximum frequency index in the predefined domain. This modification, which provided by GPSO enhance the diversity of the problem domains in order to avoid early convergence to local minimum. The violated updated positions must have applied to equation 10. Pseudocode of GPSO manipulation as follows:
1. Set g=1 , where g is the iter. #
2. Set u, and v integer numbers, calculate EI = floor (0.75*t)
3.Update iteration weight w= (u-v)/EL
4.Set j=1 to s
4.1. For Q=1 to X update velocity
4.2.Calculate particle new position x_{jd}^{t+1}
4.3. if x_{jd}^{t+1} =Int [x_{jd}^{t+1}]
Set x_{jd}^{t+1} = x_{jd}^{t+1}
Else x_{jd}^{t+1} = floor (x_{jd}^{t+1})
4.4. if Q value in $x_{jd}^{t+1}$of n_i > index value of D_{ni}
Generate r =[0,1]
Set x_{jd}^{t+1} = r * x_{jd}^{t+1}
Else x_{jd}^{t+1} = x_{jd}^{t+1}
5. Return Pj.
6. j=j+1
7. Repeat step 4.3 to step 4.4 till j=s
8. go to exchange process.
In the following process the execution of the exchange procedure achieved into two steps. The first step is to mark the violated Q's in sequence, then calculating the penalty cost for each violated pairs of nodes. The second step incurred through exchanging procedure, which depends on the penalty cost rank, and the preceding place of the Q's of the delivered structure $\forall P_j$ in the swarm.
1. Set j=1 to s
2. Read the structure of P_j $\forall n_i \in N$.
2.1. For every Q $\forall n_i$ in P_j Check constraint violation

$x_{fn_i} + x_{gn_h} \leq 1 \quad \forall n_i n_h \in E, f \in Dn_i, g \in Dn_h \ , i \neq h$: $|f - g| \geq R_{n_i n_h}$

2.2. Mark violated Q in sequence till Q=X for P_j
3. Calculate the penalty cost for each violated paired of nodes in 2.2
4. Start exchange procedure
4.1. Rank the violated paired of nodes in a descending order according to penalty cost obtained in step 3.
4.2. Remove the Q's index in order according to the rank in step 4.1, and replace with new index $\forall n_i$ in P_j
5. Return P_j.
6. j=j+1.
7. Repeat step 2 to step 6 until j=k.

The proceeding step of the proposed GPSO algorithm provide a high degree of guarantee for exploring the search space well. This achieved in the search space exploration step, which exposed in the following pseudocode Search space exploration pseudocode If new p_{jd} < old p_{jd} $\forall P_j$, j=1 to k
Set p_{jd} = new p_{jd}
If p_{jd}< p_{gd}
Set p_{gd} = p_{jd}
If new p_{gd} = old p_{gd}
Set p_{gd} = new p_{gd}

The proposed GPSO algorithm repeated till the stopping criterion met, which depends on the maximum number of iterations.

6. benchmark instances

This section introduces the CALMA project benchmark instances, which used to evaluate the performance of the proposed GPSO algorithm. In the CALMA project two sets of problem instances were used (available on the FAP website). These problems have all the characteristics of the MI-FAP model. The first set contains five instances for CELAR. The second set are six GRAPH instances, which are random instances, generated by a group of researchers from Delft University of Technology, and have the same characteristics as the CELAR instances. In CALMA instances, each link has one parallel link, and for each frequency available for a link there is one and only one frequency of its parallel link that satisfies the required

distance constraint. Also, the benchmark not only has minimum distance constraints, but also the instances contain equality constraints, to model that two frequencies at a fixed distance have to be assigned to the corresponding vertices. These characteristics provide the possibility to reduce the size of the instances to half the original size whenever that may be profitable. Table 1 summarize the CELAR, and GRAPH networks construction of the MI-FAP instances.

TABLE. 1 *CELAR AND GRAPH BENCHMARKS DATASETS*

Instances	Interference constraints	No. of nodes	Optimal solution (Range)
CELAR6	5744	200	3,389
CELAR7	2866	400	343,592
CELAR8	5744	916	262
CELAR9	4103	680	15,599
CELAR10	4103	680	31,517
GRAPH5	1134	200	293
GRAPH6	2170	400	16,020
GRAPH7	2170	400	5,990
GRAPH11	3757	680	30,312
GRAPH12	4017	680	15,208
GRAPH13	5273	916	49,205

The parameters of GPSO are set as follows: The inertia weight value w changed from 1.5 to 0.1 according to the following formula $w = (x-y)/$ every iter. where, x=1.4, y=0.2, and every iter= floor (0.75* iteration number). The self-confidence, and swarm confidence values are set $C_1 = C_2 = 0.5$. Number of particles in the swarm $N = 50$, and the number of runs is 50, while the number of iterations is 300 for each run.

7. GPSO Computational Results

In this section, the provided GPSO algorithm is applied on the benchmark problems previously introduced, and compared with the results of the related works for MI-FAP based on tree decomposition in [27], Russian doll search in [28], genetic algorithm [29], and other related works based on simulated annealing in [30], and finally point approximation in [14]. GPSO algorithm has been implemented as a project in labview programming, which consists of eleven progams. The instance name, optimum solution, and the best obtained solutions for various related works against GPSO are summarized in table 2. The optimal solution range shown in bold, while a dash "-"means the results could not obtain.

TABLE. 2 *GPSO COMPUTATIONAL RESULTS VERSUS RELATED WORKS*

Instance	GPSO	TP [27]	RD [28]	GA [29]	SA [14]	PR [30]	Optimal Range
CELAR06	3,351	3,389	3,389	3,389	3,671	4,564	3,389
CELAR07	343,589	343,592	343,592	343,593	567,949	831,926	343,592
CELAR08	262	262	--	262	276	533	262
CELAR09	15,571	15,571	15,571	--	15,571	15,770	15,599
CELAR10	31,516	31,516	31,516	--	31,516	31,517	31,517
GRAPH05	219	221	221	221	223	452	293
GRAPH06	4115	4,123	4,123	4,138	4,189	15,047	16,020
GRAPH07	4,222	4,324	4,324	--	4,324	14,183	5,990
GRAPH11	3,080	3,080	3,080	3,126	3,513	14,692	30,312
GRAPH12	11,827	11,827	11,827	--	11,827	17,372	15,208
GRAPH13	10,110	10.110	10,110	10,234	11,130	41,784	49,205

The results of IPSO shown in table 2 show the high performance of the introduced algorithm for obtaining the best solution for all bench marks with minimum number of violated interference constraints. It is obvious that GPSO beat on the SA algorithm [30], and PR in [14] in all CALMA instances. Moreover, the GPSO algorithm, delivered a solution for CELAR08, which RD algorithm in [28] didn't find. Also, the modified GPSO support solution for CELAR09, CELAR10, GRAPH07, and GRAPH12, which didn't achieve by GA in [29]. Unless otherwise stated, all the running times are in given in seconds. They include tasks like reading data from files, and computational procedures.

TABLE. 3 *STATISTICAL RESULTS OF GPSO*

Instance	Best	Worst	Mean	Percentage No. of using r / Run	CPU time /run
CELAR06	3,351	3,425	3,365	8.16%	185
CELAR07	343,589	343,850	343,599	19%	194
CELAR08	262	276	266,5	23.7%	235
CELAR09	15,571	15,596	15,580	17%	217
CELAR10	31,516	31,523	31,518	15.4%	201
GRAPH05	219	227	221	37%	99
GRAPH06	4,115	4,211	4,125	13.3%	93
GRAPH07	4,222	4290	4,235	12.7%	103
GRAPH11	3,080	3,151	3,051	9.9%	148
GRAPH12	11,827	11,990	11,850	13.7%	145
GRAPH13	10,110	10,315	10,189	21.9%	230

8.Conclusion

This paper interested in the problem of frequency assignment problem in the context of minimum interference. After having introduced an overview and the model formulation of the problem we have provided a vision for tackling the problem. This followed by producing the sequence of optimal minimum interference plan using an GPSO algorithm, which is considered as a modified adaptation of the PSO algorithm by adding a new criterion of particles update strategies, guided swarm particles initialization instead of random one is introduced. Furthermore, the exchanging procedure for violated nodes indices is introduced. These modifications improve the global optimization stability of the search results, enhance the universality and robustness of the algorithm, and improve the convergence rating and the convergence speed. The experimental evaluations using standard benchmark problems showed that for most of the problem instances, this GPSO algorithm can find better or equivalent solutions compared with related optimization methods. The

provided GPSO algorithm needed to be studied for future work under the assumption of uncertainty environment. Also, the FAP may be tackled as a multi objective using the GPSO algorithm for more investigation.

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