Performance Optimization of the Multi-Pumped Raman Optical Amplifier using MOICA

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***Abstract*—In order to achieve the best gain profile for multi pump distributed Raman amplifiers in Wavelength Division Multiplexing (WDM) transmission systems, the power and wavelength of pumps, the type of pumping configuration and the number of pump signals are the most important factors. In this paper, using a Multi-Objective Imperialist Competition Optimization Algorithm (MOICA) with lowest power consumption and lowest number of pumps, we propose the most uniform gain profile for two types of pumping configurations in S- band and compare the results. Considering the design conditions including the type of pumping configuration, fiber length, fiber type and number of pump signals and using the multi-objective algorithm, we propose a method which can be used to achieve a gain level in which the amplifier has the lowest power consumption and lowest gain ripple. According to this, we can design a powerful WDM transmission system by Distributed Raman Amplifier (DRA) with a good performance and efficiency.**

Keywords—Raman amplifier; ICA; WDM System; Optical fiber; Multi-objective Optimization

I. Introduction

Distributed Raman fiber amplifier is a powerful and hopeful technology for telecommunication systems with high capacity and long path line. It uses the transmission line as a medium to create the Raman gain. Especially in WDM systems in which the simultaneous strengthen of multi-channel light wave signals is required, it yields a magnificent increase in the extent and capacity of the light wave systems. [1-3].

Raman amplification is based on stimulated Raman scattering (SRS), which is a non-linear effect in signal transmission through optical fiber. It results in an amplification of the optical signal, assuming that the pump signal enters the fiber with a correct wavelength and power [2-4].

One of the most recent improvements in the Raman systems is the multi-pump distributed Ra-man amplifier. It causes the bandwidth extent and gain profile uniformity at the desired bandwidth, which is very important in WDM systems.

In this paper, a backward pump structure in S-band is used. In this structure, the noise sources have the least impact on the amplifier performance. Furthermore, although it can be used in C &L –bands, in the S-band, the Raman amplifier gives the superior results compared to the other optical amplifiers. The structure of a forward pump and seven backward pumps are also used in implementing the optimization algorithm to emerge the effect of pump configuration. Various methods, such as Genetic Algorithm (GA), multi-population genetic algorithm and firefly algorithm are employed to optimize the performance of distributed Raman fiber amplifier [5]. However, the Imperialist Competition Algorithm (ICA) is a stronger tool compare to the other designing methods. The results of four optimization methods for reducing the gain ripple with the same number of iterations are reported in Table 1. As seen in this table, the result of ICA method has the lowest value. It is worth mentioning that according to the random nature of the algorithms used in Table 1, they are applied five times and then the average of results is compared in Table 1.

In this paper a multi-objective imperialist competition optimization algorithm is used to have a uniform gain profile with lowest gain ripple and minimum consumption power of pumps .the results are compared with other optimization algorithms that are used in other works in this field.

In most of related works only the gain ripple is optimized and a multi-objective optimization algorithm is not used, but in this paper the number and power of pumps are optimized to achieve the best gain profile in a determined gain level with minimum consumption of power .and also by using the suggested method in this paper the best gain level with minimum of gain ripple and consumption of power can be found for a Raman amplifier with a specified configuration of pumps. So the recommended method is very useful in designing of multi-pump distributed raman amplifier.

The rest of this paper is organized as follow: in Section 2, the mathematical model of Raman amplifier used in numerical simulation is presented. In Section 3, the MOICA method used in this article to optimize the designing process is explained. The result of numerical simulation is then in Section 4 and finally, Section 5 concludes the paper.

II. The Mathematical Model of a Raman Amplifier

A simple scheme of a Distributed Raman Amplifier (DRA) is depicted in Figure 1. As seen in this figure, it is composed of an optical fiber having the length L as a medium gain and forward (co) and backward (counter) pumps.

$$\frac{dP_\nu^\pm}{dz} = \mp\alpha_\nu P_\nu^\pm + P_\nu^\pm \sum_{\mu\rangle\nu} \frac{g_{\mu\nu}}{A_{eff}} (P_\mu^+ + P_\mu^-)$$
$$-P_\nu^\pm \sum_{\mu\langle\nu} \frac{g_{\mu\nu}}{Ae_{ff}} (P_\mu^+ + P_\mu^-)$$
(1)

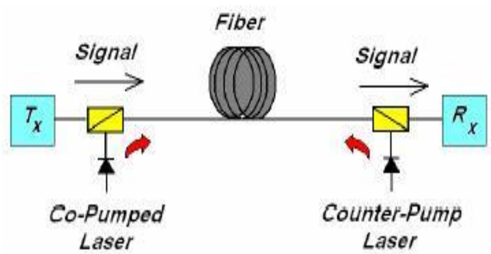

Fig. 1. Scheme of a DRA used in optical communication system [6]

where ν and μ indexes indicate the light frequencies and + and – indexes show the backward and forward signal propagation. P_ν and αν represent the optical power and attenuation coefficient, respectively and $g_{\mu\nu}$ is the Raman gain at the frequency ν caused by the pump at frequency μ. Aeff is also the effective cross section of optical fiber. The related diagram is shown in Figure 2 [8].

The equation 1 includes the signal-signal, signal-pump and pump-pump interactions. However, the interactions such as amplified spontaneous emission (ASE) and temperature dependence are neglected because they do not have a significant effect on the optimization process.

In this paper, we use the “true wave reach low water peak” fiber because it has a low loss com-pare to the other types of optical fibers in water peak area. This limitation is used for choosing the pump wave length. The corresponding Raman gain diagram is shown in Figure 2.

Using solutions of Equation 1, a quantity named on-off Raman gain is often achieved for every signal channel at the desired frequency band. This quantity is defined as the signal power increase at the amplifier output when the pumps are turned on. Therefore, for small signals we have:

TABLE I. THE RESULT OF DIFFERENT OPTIMIZATION ALGORITHM IN BACKWARD PUMPING CONFIGURATION

Algorithm	Gain Ripple in Run1	Gain Ripple in Run2	Gain Ripple in Run3	Gain Ripple in Run4	Gain Ripple in Run5	Mean
GA	0.4272	0.3670	0.5025	0.2906	0.6828	0.4540
Firefly	1.0203	0.6879	1.0802	1.2400	1.3978	0.9449
multi population -GA	0.2532	0.7295	0.3323	0.4372	0.5344	0.4573
ICA	0.4553	0.1989	0.2384	0.3048	0.3046	0.3004

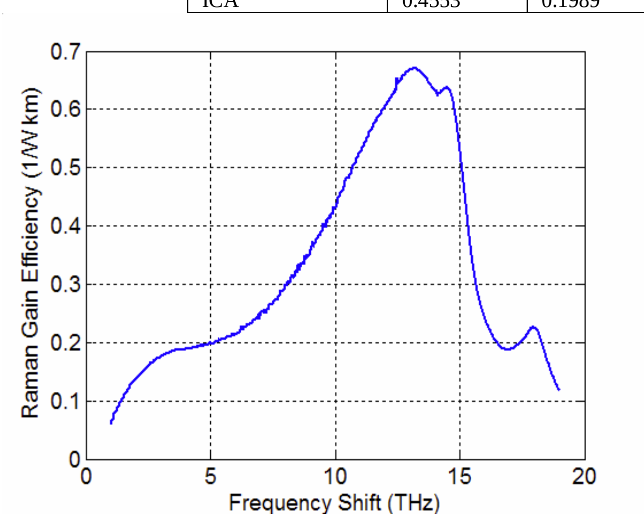

Fig. 2. Measured Raman gain efficiency curve(λp=1420nm) [8]

$$Gon-off = \frac{p_s(L) with pumps on}{p_s(L) with pumps off} \quad (2)$$
$$= \exp(C_R L_{eff}[P_P{}^+(0) + P_p{}^-(L)]$$

In which L_{eff} is the fiber effective length in which most of the Raman gain is created

$$L_{eff} = \frac{[1-\exp(-\alpha_p L)]}{\alpha_p} \quad (3)$$

These equations can be used to estimate the appropriate pump power to achieve a given gain with acceptable fluctuations. For transmission of WDM systems, the Raman amplifiers should be designed so that a uniformed and wide gain spectrum is created, having the conditions and limitations such as the number of pumps, the signal band range and the type of fiber used. Thus, in designing the con-figuration of Raman amplifiers pumps, the role of optimization algorithms is very important.

The multiple-objective optimization algorithm used in this paper, improves the on-off Raman gain fluctuations with the least pump power consumption.

III. MULTI-OBJECTIVE OPTIMIZATION

The multi-objective optimization consists of some different and even contradictory aims that should be, minimized or maximized at the same time. Some equal or unequal constraints should be considered by the solutions. A multi-objective optimization can be expressed by the following formulas [9, 10]:

$$Minimize\ \vec{f}(\vec{x}) = [f_1(\vec{x}), f_2(\vec{x}), \dots, f_K(\vec{x})]$$
Subject to:
$$g_i(\vec{x}) \le 0\ i = 1,2,\dots,m$$

$$h_i(\vec{x}) \leq 0 \; i = 1,2,\ldots,p$$

In the above equations $\vec{x}$ is the n dimensional decision vector, f(i): $R^n \rightarrow R$ i=1,2,…,k are the objective functions and $g_i,h_j : R^n \rightarrow R$,i=1,2,…,m j=1,2,…,p are limitations and constraints.

A solution vector is called a Pareto optimal vector if a better solution cannot be found which is more optimal in an objective function and operates appropriately in the other objective functions.

In this concept, instead of finding an optimal solution, a set of optimal solutions is found which is called the Pareto optimal set or Pareto optimal solutions. A vector corresponding to an optimal Pareto solution is mentioned as a non-dominated vector. To draw the aim function, a set of all solutions which are non-dominated are used that are called the Pareto forefronts [11, 12, 13].

At single-objective optimization, there is only one search space while in multi-objective optimization, there are two search spaces including the variables and the objectives search space. There-fore, diversity can be defined in either space. In multi-objective optimization, those solutions that are not close to Pareto forefront are not suitable. If the objective functions are not in the conflict, the Pareto optimal set will have a member. Therefore, the optimal Pareto forefront set exists only if the objective functions are in conflict with each other.

The solution s1 dominates s2 if and only if the two following conditions are satisfied:

1) Considering all the objectives, the s1 solution is better or the same as s2 solution.

2) Solution s1, is strongly better than s2 at least in one objective.

If s1 dominates s2 according to the above mentioned conditions, it is considered as a better solution. The theory space includes a set of all solutions which do or do not dominate each other. A set of all solutions which do not dominate each other is called the Pareto forefront solutions. These non-dominant solutions are connected by a curve which is called the Pareto forefront optimal set. Figure 3 represents the Pareto forefront solutions for a problem with two opposite objective functions.

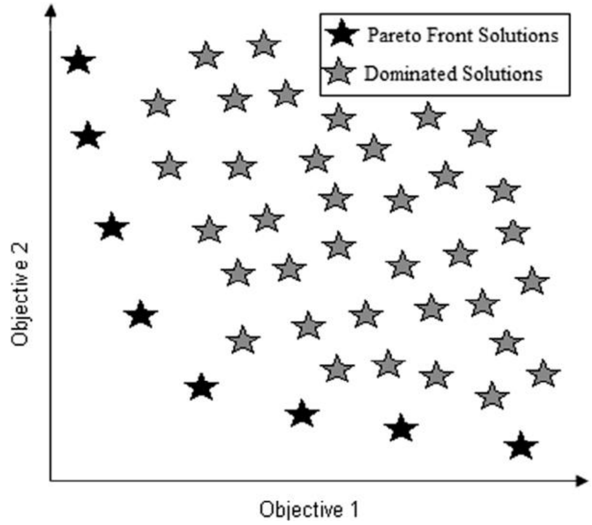

Fig. 3. Pareto-front solutions[14]

B. Fast sorting of non-dominants

The NSGA-II and MOPSO algorithms are two predominant multi-objective evolutionary methods in which the individual evolution is performed using the fast sorting of non-dominants and crowded distance.

The fast sorting of non-dominants is a strategy which ranks the solutions according to the objective function. If the crowded distance increases, the algorithm can distinguish between the two per-sons with the same rank. Those solutions with grade one are called the Pareto forefront and no solution can dominate them. Those solutions with the grade two will be defeated by only one solution. This process is performed on all solutions and all solution ranks are determined.

This sorting is done in two steps. At the first step, some solutions with grade one are identified. At the second step, the other solutions are identified (see Figure 4). Every solution is compared with the other solutions and if there is any solution which dominates it the corresponding counter variable is increased by one unit. In addition, all of the solutions which are defeated by this solution are saved in an array named Sp. Thus, at the end of the first step, the Pareto forefront set is identified. The number of times that one solution is defeated is saved in variable n_p. Therefore, there is a solution, with n_p=0 in forefront Pareto F1. At the second phase, rank of the other solutions is achieved using the information from the first step.

C. Imperialist competition algorithm

The imperialist competition algorithm begins with producing an initial population of possible solutions each of which called a country. Based on its value, every country can be a colony or an imperialist (an emperor). The strong countries are considered as imperialists who control some weaker countries as emperors. This algorithm is based on the competition among the emperors. The weak emperors would finally collapse and hand over their colonies to the stronger emperors. Finally, the algorithm converges to a single emperor. In this case the best solution of the optimization problem is achieved.

At the first step of the imperialist competition algorithm, the emperors are created. Every imperialist receives some colonies according to its power. This process is done according to the equations 4 and 5 which is shown in Figure 5. The more powerful imperialists would have a higher number of colonies while the less powerful imperialists would have a less number of colonies.

$$P_i = \left(\max_{1\le j\le N_{imp}}\{C_j\}\right) - C_i \qquad (4)$$

$$NC_i = round(\left|\frac{P_i}{\sum_{j=1}^{N_{imp}} P_j}\right| \times [N - N_{imp}]) \qquad (5)$$

Where C_i is the cost of the i*th* emperor, P_i is the power of the i*th* emperialist and NC_i shows the number of colonies belong to the i*th* imperialist.

After initializing the empires, the absorption process starts. Figure 6 represents how countries move toward the corresponding empire. This movement is according to Equation 6. In the process of movement of colonies toward the imperialists, there is always a possibility that a colony reaches to a better condition compared to the emperor. In such cases the colony would be replaced by the emperor and would be converted to an imperialist. The process continues with the new empire and the colonies which are under the control of the previous empire would move toward the new empire.

$$X_{new}=X_{old}+ \beta\ d \qquad (6)$$

After the process of power absorption, every empire would be calculated based on the total power of that empire and its dependent colonies. However the effect of colonies is negligible. The power is calculated as follow:

$$T.C_n = Cost(imperialist_n) + \xi\ mean\ \{Cost\ (colonies\ of\ empire_n)\ \} \qquad (7)$$

where ξ is a constant in the open range of zero to one.

The competition between the empires is the most important challenge in which each of them tries to take the other`s colonies. While the weaker empires are trying to survive, the stronger ones are expanding their territory. The competition between the empires is stimulated by separating colonies from the weaker empires and giving them to the stronger ones. The probability of ownership of every emperor is proportional to its power. When an empire loses all of its colonies, it would fall and be eliminated. Finally, a single empire would remain which controls all of the countries. When all of the countries and even the emperor have the same situation, this is the sign of reaching to the answer of optimizations problem.

D. multi-objective imperialist competition algorithm

There are two fundamental issues in development of a MOEA:

1) The competence of each individual based on all of the goals

2) Maintaining the diversity of the final solution

In order to determine the competence of each individual in this algorithm, the method of fast sorting of non-dominants and a new initiative method named sigmoid method is used. In previous MOEAs, the crowded distance was used for comparing the individuals which did not provide a quantitative measurement. In the algorithm used in this design, a quantitative measurement is provided. This measurement is important in determining the empire countries and the power of imperialist countries and estimating the total power of empires for competition of imperialist.

Firstly, rank of the countries is defined by non-dominant rapid sorting method according to all goals. All of the countries situated in the Pareto optimal front have the rank one and the emperors are selected from this collection which has a strong effect on convergence and diversity of solutions. The more the number of goals is, the more this effect would be.

After identifying the rank of each country the sigmoid function is applied and the competence of every individual is estimated. In the main ICA, each country is assigned on the basis of objective function power. In this method, the power of each country is based on all the targets (or in the other words on the multi-objective). Therefore the following assumptions should be considered:

Assumption 1: the power of every country is related to its rank. According to this, the weaker countries have the higher ranks and the stronger ones have the smaller ranks.

Assumption 2: those countries with the same ranks are compared by the sigmoid method.

After applying the non-dominant rapid ranking method if a country has the rank C its power is calculated as follow

$$Fitness_c = \sum_{j=1}^{D}\left[\frac{F_j(C)}{\sum_{i=1}^{N_{Rank(C)}} F_j(i)}\right](Rank(C)-1)\times D$$

$$Power_c = \frac{1}{Fitness_c} \qquad (8)$$

In the equations (8), D is the number of goals, f (i) is the value of the *i*th object and N Rank(c) is the number of the countries with the rank C. The power of the c*th* country is shown by $Power_c$ and after calculation; the related amount of fitness is achieved. The fitness amount of a function is the all target values and rank of the individual. At the first part of equation (8), amount of all objectives is normalized based on the related amounts of objectives of all of individuals having the same rank. The normalization is done according to the rank in which the solution is located not according to the total space of the search. The second part of that equation highlights the role of the rank in amount of fitness and even the best solutions in higher ranks (the weaker solutions) have more fitness (of course, in the minimization problems) compare to the bad solutions that are in the lower ranks. Therefore, the normalization according to the rank leads to a more reliable and effective quantitative comparison of the solutions with the same rank. The normalized amount of all goals is reported as fitness.

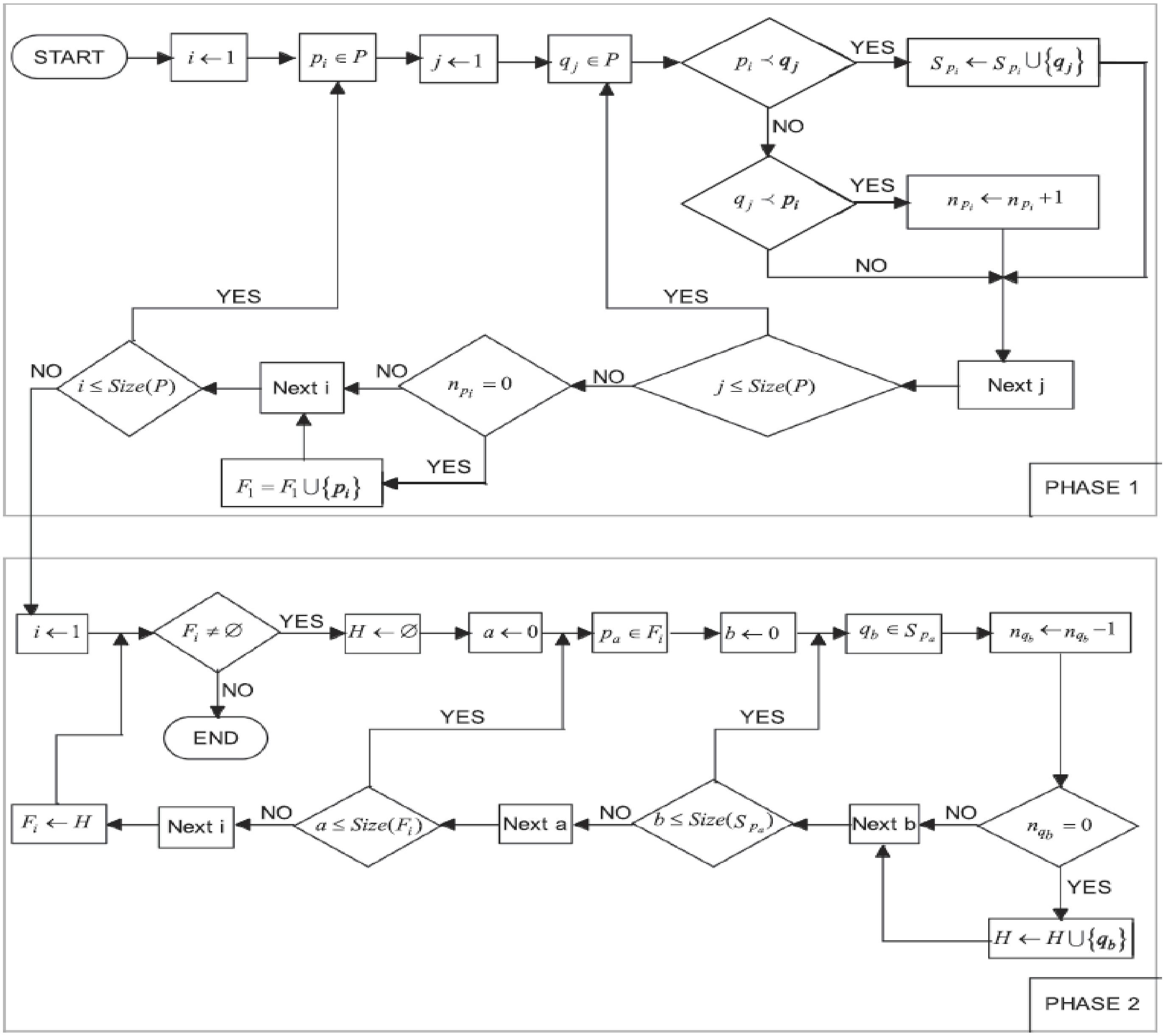

Fig. 4. Fast non-dominated sorting[14]

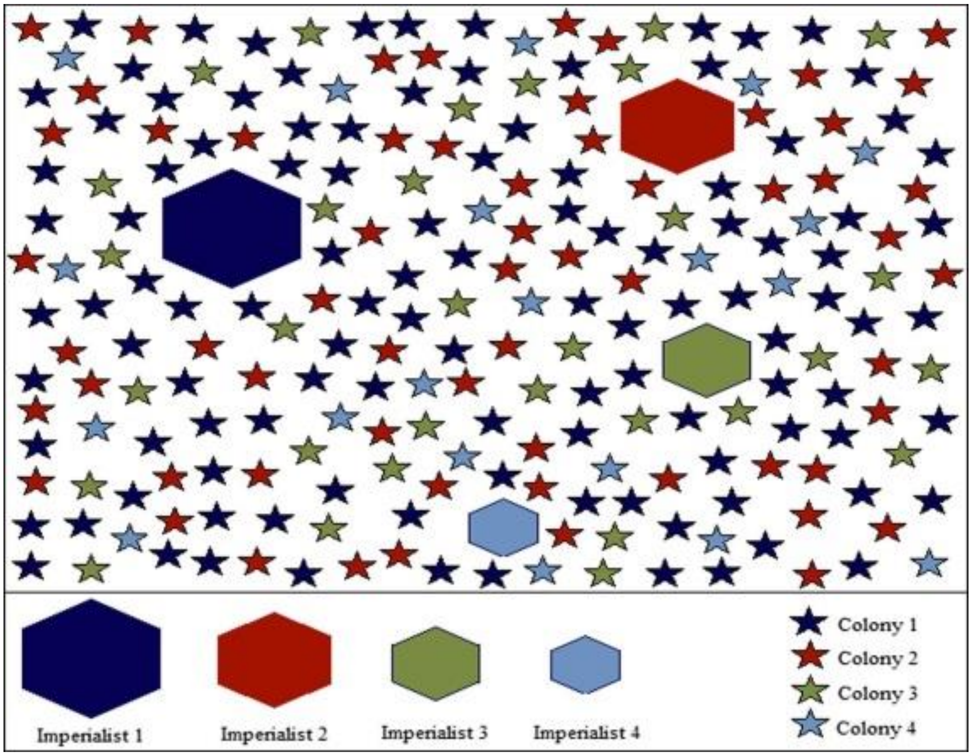

Fig. 5. Creation of Imperialist

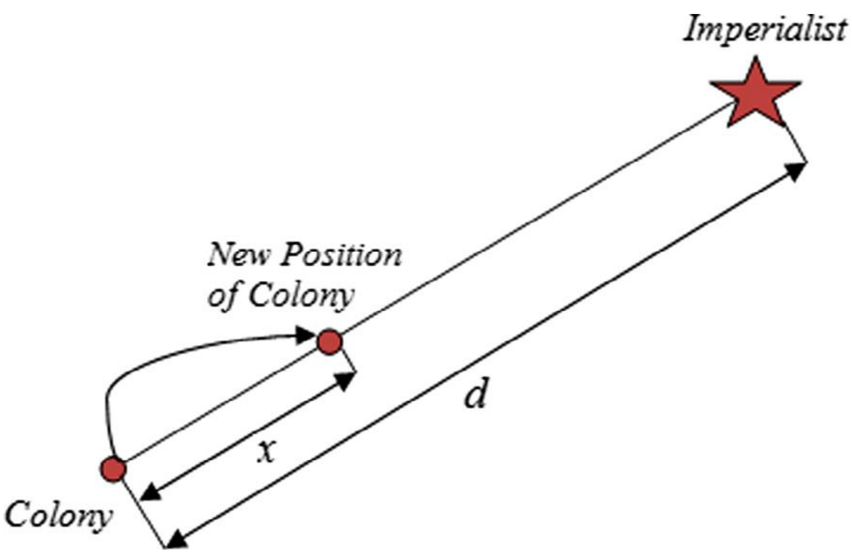

Fig. 6. the method of movement of countries toward the related empire

After estimating the power of all countries the multi-objective imperialist competition algorithm acts similar to its single objective version. For example, N_{imp} of the most powerful countries are selected as emperors. The rest of the countries are divided between the empires based on their powers. The share of empire from colonies will be calculated by the following equation

$$P_n = \left| \frac{Power_n}{\sum_{i=1}^{N_{imp}} Power_i} \right| \quad (9)$$

It should be noticed that to calculate the power, all of the countries are collected in a set and their ranks are calculated according to the objectives and using the non-dominant rapid ranking method. Then, their corresponding power is calculated using the sigmoid method. After calculating the power, the countries are divided again based on their previous situation among the emperors.

The flowchart of the multi-objective imperialist competition algorithm is shown in figure 7

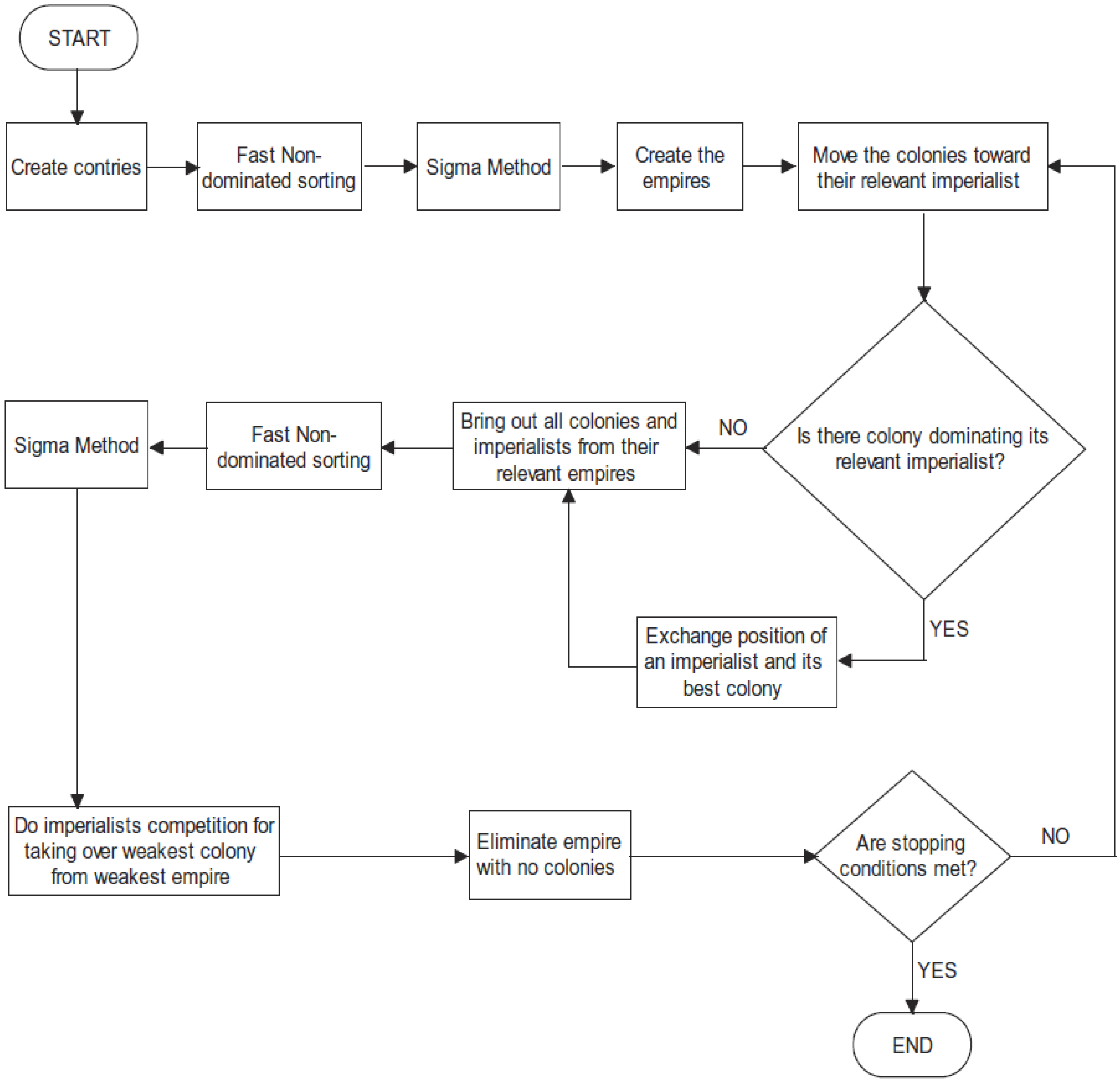

Fig. 7. flowchart of multi-objective Imperialist competition algorithm

IV. Simulation and Results

In this study, the equation (1) is firstly obtained for each signal wavelength and pump and for simulation of Raman Effect it is solved using the numerical methods as coupled equations. Then, using the multi-objective imperialist competition algorithm [14], suitable values for power and wave length of pumps are found so that the value of gain ripple and the total using power of r pumps in S-band with bandwidth of 80nm are both minimized at the same time.

The input signal channels are selected from 1460nm to 1530nm with spaces of 5nm. The power of each input signal channel is 10mW and the fiber length is 100 kilometers.

The gain optimization is done around a constant and given number. This number is also considered as one of the variables that the optimization algorithm should find its appropriate size. Thus, the calculation formula of gain ripple is considered as one of the goal functions in the optimization algorithm in the form of equation 10. The second objective function in this multi-objective optimization is equal to the set of pumps powers.

$$\text{Max}\ \{\text{Abs}\ [\text{gain}\ (\lambda s1)\text{-g0},\ \text{gain}\ (\lambda s2)\text{-g0},\ldots,\ \text{gain}\ (\lambda s16)\text{-.g0}\ ]\} \tag{10}$$

As mentioned in the optimization section, using the multi-objective optimization algorithms we finally reach to a set of suitable answers called the Pareto optimized forefront. Figure 8, shows the Pareto diagram for the final case. The optimized gain level (go) of 3dB is achieved and the fluctuations around it have been reported in Table 2. In Figure 8, two goals are considered as two dimensions which are independent from each other. In the other words one of our theory spaces is two dimensional.

This algorithm is considered for optimization with limitation for pump signal which is used as follow:

p_1-p_8(0-70mw) و λ_1-λ_8(1359-1450nm)

The results are reported in Table 2. The number of iterations of algorithm for finding the optimum answer was 1150. The initial number of countries was 400 and among them, 20 countries were selected as emperors. 5 imperialist were finally remained. The number of Pareto forefront members was 180 at the last iteration. Among them, the information of 5 selected imperialist is shown in the Table 2. The number of algorithm iterations was determined by trial and error according to the hardware limits for test. Verifying the information related to the locations of 180 members of Pareto fore front members, the similarity and vicinity of their locations reveal that the algorithm has converged and found the optimal solution.

As seen in Table 2 and Fig. 9, in imperialist 1, the ripple of 0.09402 dB around the gain level of 3db is achieved with total pump power of 255.2 mw which is the minimum amount of gain ripple among five of the best algorithm answers. In imperialist 4, the gain ripple of 0.24708 dB is achieved with total pump power of 244.44213 mw which is the minimum amount of the used pump power among the selected answers. In this case, the pump power rate is decreased compared to the previous structure while the gain ripple is increasing. Now, according to the design requirements and importance of each parameter, one of the available pump structures in Table 2 is selected to implement the desired Raman amplifier. By comparing the results of Table 2 in which the least value is 0.09402 with that of [15] which has the same condition as this paper for simulation except that it uses the PSO optimization algorithm, it is concluded that the gain ripple is decreased compared to the reported rate of 0.136. Furthermore, as seen in Table 2, since the power of the 8th pump is zero, the number of pump signals in all of five imperialist is decreased to seven signals. It means that in ICA algorithm, the desired ideal answer could be achieved using a fewer number of pump signals which is an advantage of the employed method. Assuming that the noise effect is negligible and in the desired amplifier design, the pump configuration is selected as one forward pump and 7 backward pumps, the obtained results are reported in Table 3.

According to Table 3 and Figure 10, it is obvious that in this configuration, more uniformed gain profile can be achieved with fewer pump power. For example, the second answer in Table 2 which is related to the configuration of 8 backward pumps has approximately the same gain ripple compared to the second answer in Table 3.

Even in the second case, the rate of fluctuations is lesser. However, the rate of consumed power in the second case is 32.5 mW lesser.

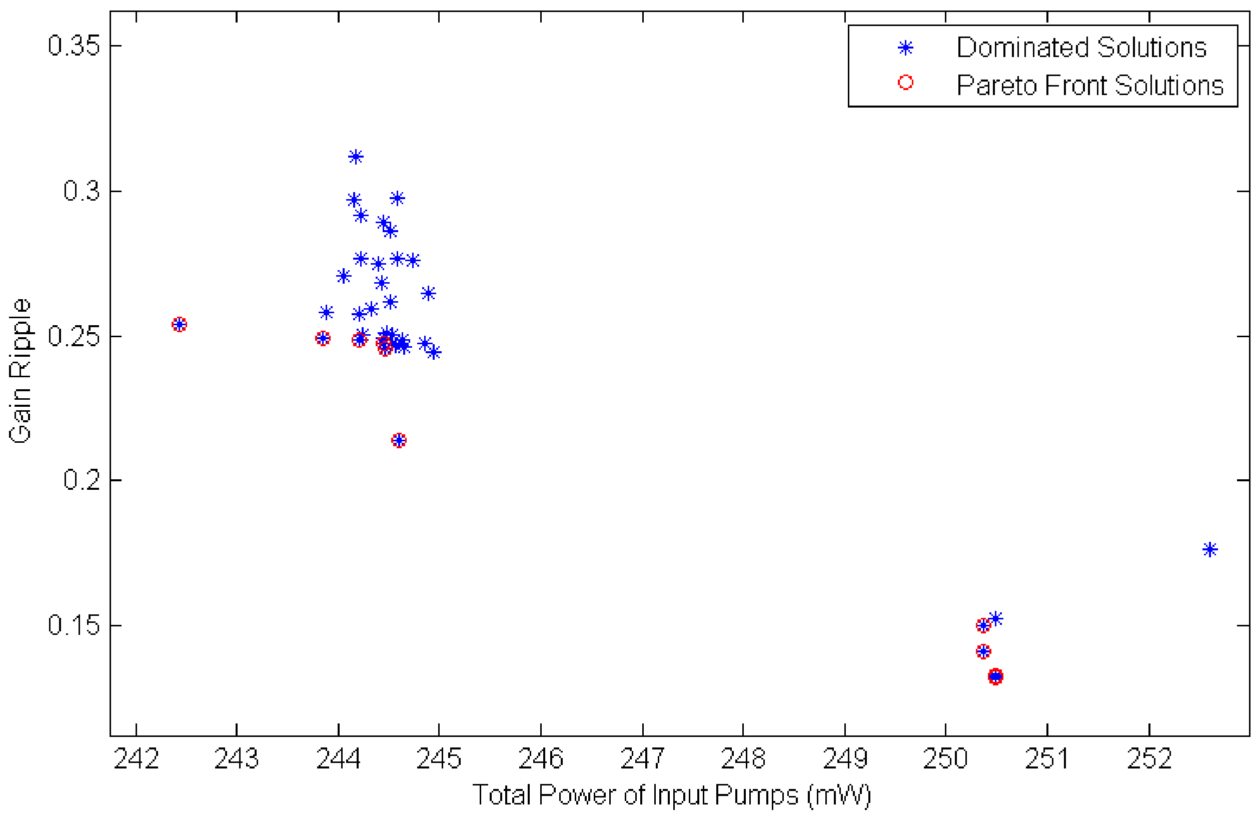

Fig. 8. Pareto diagram for final case

TABLE II. THE RESULT OF OPTIMIZATION WITH MULTI-OBJECTIVE ICA ALGORITHM IN BACKWARD PUMPING STRUCTURE

	8 pump powers P_j (mW) and their Frequencies λ_j (THz)								total power of input pumps (mW)	gain ripple (dB)
Imp 1		1	2	3	4	5	6	7	8	255.2031	0.09402
	P	39.3061	30.02521	0.696911	54.74846	16.50323	56.01128	57.91191	0		
	λ	218.8645	217.0124	220.4194	208.8315	219.7974	214.3313	210.7513	0		
Imp 2	P	62.39576	54.53276	20.88627	45.83234	49.01956	4.996665	12.826	0	250.4893	0.13247
	λ	209.4038	210.9225	219.0399	215.9991	217.7805	206.8966	213.4935	0		
Imp 3	P	68.26442	36.63109	7.186206	53.70375	19.24751	36.95877	22.60885	0	244.6006	0.2136
	λ	210.9862	218.6084	206.9732	216.408	218.6216	210.0791	210.6517	0		
m p	P	37.5164	39.02661	0	67.81045	1.769148	33.67335	64.64617	0	244.44213	0.24708
	λ	217.9719	219.6433	220.3698	210.4618	218.092	209.53	213.9637	0		
Imp 5	P	50.04193	29.57433	21.50764	63.78989	43.73134	41.72416	0	0	250.3693	0.14998
	λ	216.8354	208.0884	210.9685	209.8689	218.7318	214.2194	211.1866	0		

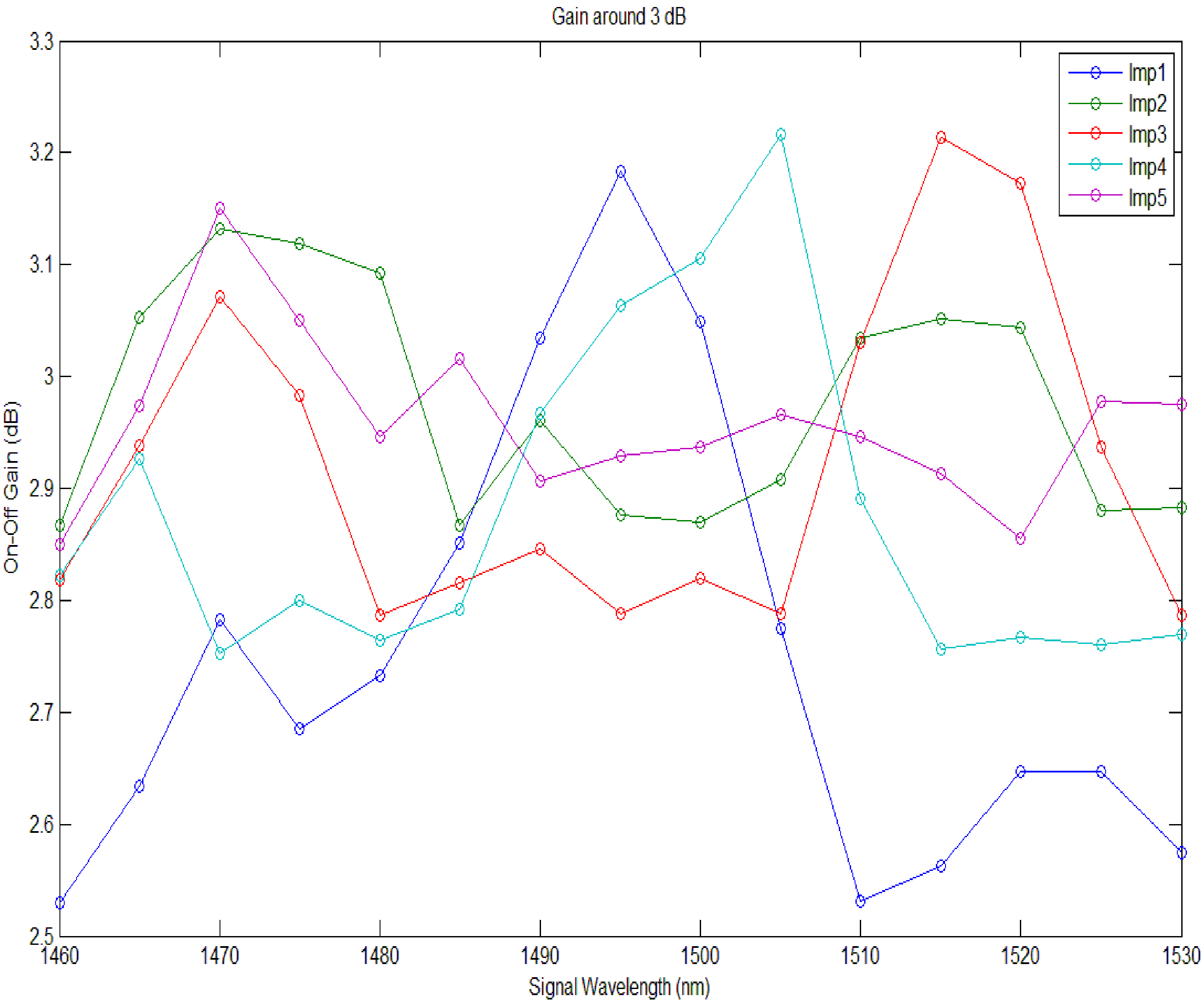

Fig. 9. The spectrum of Raman gain that achieved with multi-objective ICA algorithm in backward pumping structure

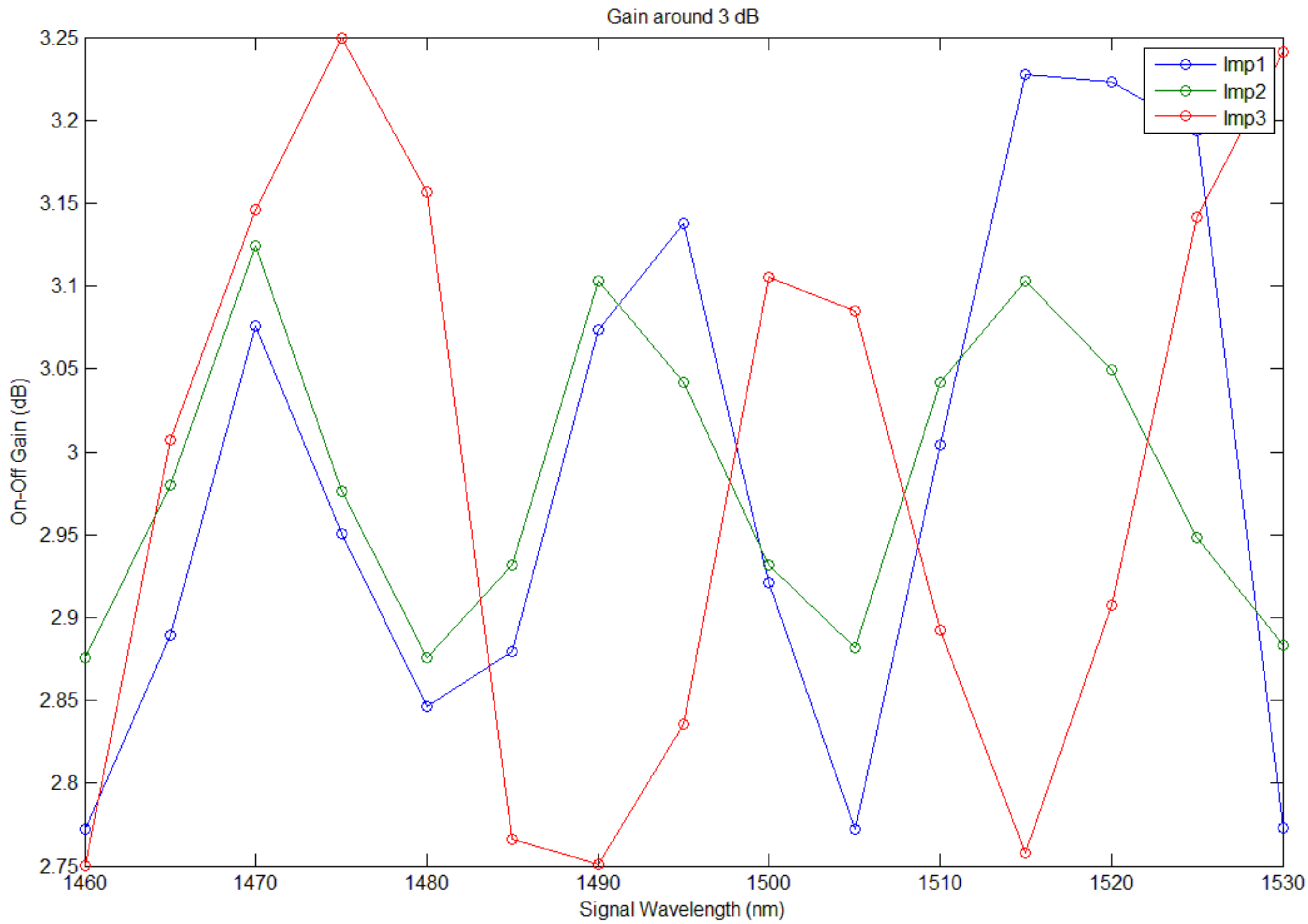

Fig. 10. The spectrum of Raman gain that achieved with multi-objective ICA algorithm in 1 forward and 7 backward pumping structure

TABLE III. THE RESULT OF OPTIMIZATION WITH MULTI-OBJECTIVE ICA ALGORITHM IN1 FORWARD AND 7 BACKWARD PUMPING STRUCTURE

	8 pump powers P_j (mW) and their Frequencies λ_j (THz) 1 Forward 7 backward									total power of input pumps (mW)	gain ripple(dB)
		1	2	3	4	5	6	7	8		
Imp 1	P	41.80618	0	66.53483	2.145349	0	0.619079	51.58809	43.10304	205.7966	0.2277
	λ	218.7108	206.8973	211.1566	206.8966	219.7067	220.5882	215.8289	209.4899		
Imp 2	P	36.84844	21.75133	25.25959	69.79903	6.913643	0.456617	7.666741	43.20697	211.902	0.1246
	λ	218.7592	211.0864	213.7549	209.6391	219.1319	220.472	210.7508	216.1991		
Imp 3	P	70	9.024821	0	38.15369	1.623326	59.97018	0.620729	25.17374	204.5665	0.2498
	λ	217.7616	213.0262	219.9269	214.5634	216.166	209.2603	207.571	208.4559		

V. CONCLUSION

In this paper, using the multi-objective optimization algorithm with the least consumed power of pump, the most uniform gain profile in S-band was achieved. The effect of pump configuration on Raman amplifier performance in optimal case was also verified. The simulation results reveal that if the noise does not interfere, the structure of one forward pump and seven backward pumps is a better design for achieving the best performance with the lowest pump power. However, in most of the researches in this field, only the gain profile is uniformed without considering any limit for the consumed power and only the backward pump structure is used. The employed optimization algorithm in this paper is a multi-objective ICA which as shown in this paper, has a high performance in optimization of Raman amplifier compared to the other algorithms in this field.

For future work the recommended algorithm can be applied in a Raman optical fiber amplifier that uses a new class of optical fiber such as a photonic crystal fiber (PCF) as a medium gain, and also MOICA can be potentially applicable to the swarm dynamics such as [16] to increase the performance of optimization.

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