Design of global positioning system (GPS) networks using different artificial intelligence techniques

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ABSTRACT

The selection of optimal GPS baselines can be realized by solving the geodetic second-order design (SOD) problem. Basically, there are two techniques to be used for selecting optimal baselines in GPS network, namely, traditional techniques and artificial techniques. Traditional techniques include the method of trial and error and the analytical method, while artificial methods include both local and global optimization techniques. The global optimization techniques, such as Genetic Algorithms (GAs), Simulated Annealing (SA) method, Particle Swarm Optimization (PSO) Algorithm, and Butterfly Optimization Algorithm (BOA), have been used recently in geodesy. In the current study, BOA has been used for the selection of the optimal GPS baselines to be measured in the field that will meet the postulated criterion matrix, at a reasonable cost. It has been tested on a GPS network. The BOA is already designed, and it determined the number of baselines that would be observed because of obtaining high accuracy. The results showed that the BOA method was more efficient than the traditional ones by 19.2%. It was better than the artificial methods in terms of length as it enhanced SA method by 21.7% and PSO method by 4.6%. Consequently, the use of the BOA is proven to be more effective and applicable.

Keywords: GPS networks; Artificial Intelligence; Butterfly Optimization Algorithm (BOA);   Second-order design problem.

INTRODUCTION

Global Positioning System (GPS) is mainly used to create a special precise geodetic network to monitor deformations and crustal movements (Dwivedi and Dikshit, 2013). GPS is an advanced technology, which plays a vital role in our daily life, whereas GPS applications are becoming increasingly important in our dynamic world (Hoque, 2016). Optimization design and optimal geodetic network play a key role in many geodetic applications (Doma, 2013), whereas the geodetic network quality is characterized by its reliability, cost, and precision. The main objective of designing optimal network and optimal observational plan is to provide high reliability and excellent precision, at minimum cost (Amiri-Simkooei et al., 2012). The optimal design of GPS networks can be attained by following the traditional approach to optimize the terrestrial geodetic networks, as follows (Grafarend, 1974): Zero-order design (ZOD), Optimum datum definition, and First-order design (FOD). Design an optimal network configuration, Second-order design (SOD): Specification of observation weights, Third-order design (THOD): Development of the existing network by removing and adding observations.

Among the four abovementioned orders of design, the SOD problem is generally discussed in literature and shown in practice. The main problem of the optimization GPS network and the traditional SOD problem is the choice of the most optimal baselines to be observed in the field (Dwivedi and Dikshit, 2013). The main objective of SOD is to determine the best economic survey movement that meets the required network optimization criteria.

The SOD identifies the observations to be made and their corresponding accuracy. Moreover, it facilitates the choice of the proper instrument and observation procedures (Yetkin et al., 2009). The technique of optimization provides the optimal weights of observation, which can then be classified into zero, small, or optimized weights. The optimized weights can also be much less than the initial weights; they are then modified by their corresponding initial weights. Baselines that achieve zero or small weight signify that such baselines must not be observed (Doma, 2013). Artificial intelligence techniques are used to analyze large amounts of data to establish an ideal GPS network design based on geometrical and financial constraints. Approaches and algorithms such as large networks and logistics include local and global optimization, which can meet the needs of GPS networking (Kota, 2018; Habeeb, 2018). Achieving optimization allows for the selection of suitable GPS baselines, and it can be realized by solving the geodetic second-order design (SOD) problem. Basically, there are two techniques to be used for selecting optimal baselines in GPS network, namely, traditional techniques and artificial techniques. Traditional techniques use trial and error and the analytical methods (Alizadeh-Khameneh, 2017). Yet, the artificial techniques encompass local optimization and global optimization techniques shown in figure (1). Lately, global optimization techniques like GA method, SA method, PSO algorithm, and BOA method have been recently introduced to geodesy (Fig (1)) (Doma et al., 2013).
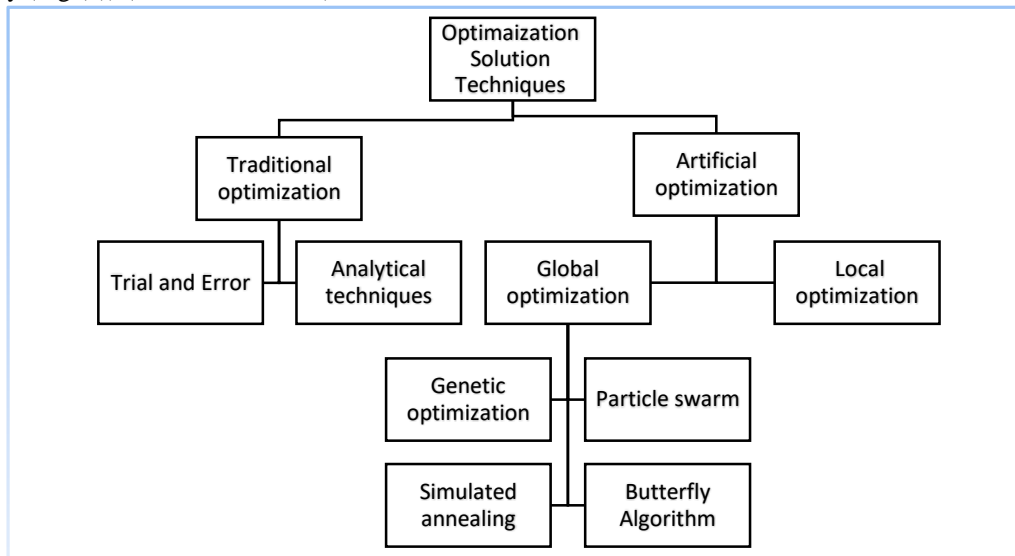

Figure 1. Optimization Solution Techniques.

LITERATURE REVIEW

In traditional techniques, Kuang (1996) used the same GPS network as in our work. After decreasing (2.00 mm) from the precision of the network, a total of 73 baselines were removed (Kuang, 1996). In artificial techniques, SA method was applied to this network, and a total of 79 baselines were removed (Faried, Doma 2013). PSO method was applied to this network, and a total of 87 baselines were removed (Doma, 2013). The optimization of a geodetic network is the act of designing a specific step, so that the end product matches the expected (optimal) design requirements. The purpose of optimization is to find a model that meets the adopted reference system's requirements/criteria (Postek, 2021).

OBJECTIVES

The main objectives are as follows:

1. Implementation of a monitoring plan to improve GPS networks using Artificial intelligence-based BOA.
2. Comparison of Artificial intelligence-based BOA with traditional methods and artificial methods such as SA and PSO to choose the optimal technique to improve the GPS network.

MATHEMATICAL EQUATION OF THE GPS NETWORK PROBLEM

The most accurate GPS-based positions are acquired when all satellites are observed as long as possible, and all baselines are measured and recorded in the network. This is extremely difficult in practice because of payments

and time. Thus, optimum survey design must be done to get the prescribed design criteria at minimum cost. In optimization problems, P is the matrix of observation weights, and A is the matrix that acts as the geometry of the network. In case the two matrices are known, the covariance matrix of the unknowns is given by (Doma and Sedeek, 2012; Doma, 2013)

$$Q_x = (A^T P A)^{-1} \qquad (1)$$

As generally stated, SOD aims to determine the weights of P (perhaps only for some "baselines" of observations) that create the resulting cofactor matrix. The cofactor matrix could be in any required form. For example, it might follow the matrix criterion of Baarda (Baarda, 1981) that leads to the regions of absolute confidence and relative circular shape, or it can simply be a diagonal matrix (although it is not possible in practice). Anyways, let us determine the degree of approximation to the required solution through applying the Frobenius norm—that provides the distance of Euclidean between matrices (Doma and Elshoney, 2011). Hence, the global problem of optimization is then pointed out as the problem of calculating the weights contained in P (Equation (1)) for which the following global minimum is obtained (Kuang, 1991 and 1996 ; Yetkin et al., 2008 and 2011 ; Doma, 2013):

$$min \, \|Q_f - Q_x\| = min \sqrt{\sum_i \sum_j ((Q_f)_{ij} - (Q_x)_{ij})^2} \qquad (2)$$

As a new strategy, some constraints can be put on the weights to be obtained in the present study. Such constraints include at least the need for some of the weights to be negative in order to delete them from the final observational plan. The solution to Equation (2) will always exist, but obviously, the attained degree of approximation to the desired matrix will be prticularly dependent on the problem itself.

A MATLAB code was adapted using BOA techniques to optimize a presolved example to asses the BOA as an artifical intelligant technique in solving SOD.

BUTTERFLY OPTIMIZATION ALGORITHM

Butterfly Optimization Algorithm (BOA) is a new nature inspired algorithm, which mimics the pattern of butterflies' food searching strategy (Arora and Singh, 2015). Butterflies act as the search agents used by the BOA to implement optimization. In BOA, it is assumed that a butterfly will release scent with different intensities according to the butterfly fitness. The scent will spread, and other butterflies can feel it (Arora and Singh, 2017). The stages of BOA are as follows: initialization stage, iteration stage, and final stage.

During each iteration process, the butterflies in the solution space take new positions. Then, their corresponding fitness values are calculated by the algorithm according to the following equation (Arora and Singh, 2015 and 2019):

$$f = cI^a \qquad (3)$$

where (f) is the amount of the scent received by other butterflies, (c) refers to the sensory modality, (I) refers to the stimulus intensity, and (a) refers to the power according to modality, which measures different degrees of absorption. The algorithm is divided into two key steps: local search phase and global search phase. At the stage of global search, take the butterfly step towards the fittest butterfly /solution g, which can be formulated as follows (Arora and Singh, 2015 & 2019):

$$x_i^{t+1} = x_i^t + (r^2 \times g^* - x_i^t) \times f_i \qquad (4)$$

where (x_i^t) is the solution vector. (x_i) is the butterfly in iteration number (t). (g^*) introduces the best currently found solution in the current stage. The scent of a butterfly is shown by (f_i). (r) is a random number in [0, 1]. The local search phase can be summed up as follows:

$$x_i^{t+1} = x_i^t + (r^2 \times x_k^t - x_j^t) \times f_i \qquad (5)$$

where (x_j^t) and (x_k^t) are jth and kth butterflies chosen randomly from the solution space. If x_j^t and x_k^t belong to the same subgroup, (r) is the random number in [0, 1]. The local and global scales exist when the butterflies search

for mating partners and foods. Therefore, a switch possibility (p) is used in BOA to switch between joint global search and intensive local search. In Figure (2), the flow chart describes the optimization stages of the BOA and the proposed approach. The computational stages of the proposed BOA are presented below, and its pseudocode is described in Algorithm 1 in Figure (3) (Arora and Singh, 2015 & 2019).
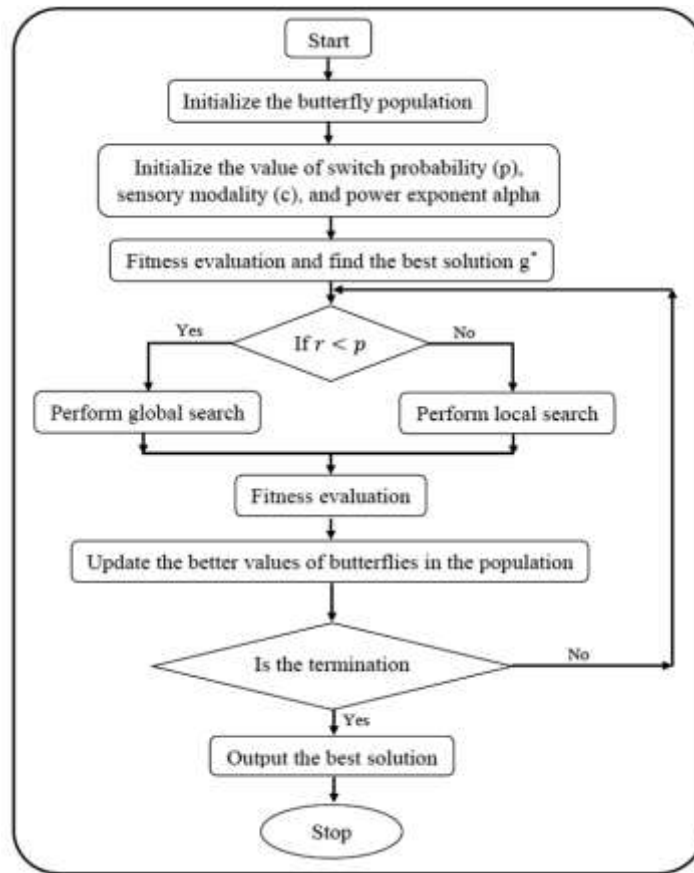

Figure 2. Algorithm 1 Butterfly optimization algorithm.

Algorithm Butterfly optimization algorithm:
1:     Objective function $f(x), x = (x_1, x_2, x_3, \dots \dots x_{dim}), dim = no. of\ dimensions$
2:     Generate initial population of n Butterflies $x_i = i = 1,2, \dots \dots n)$
3:     Stimulus Intensity I_i , x_i is determined by $f(x_i)$
4:     Define c, a and b
5:     While stopping criteria not met do
6:     for each butterfly bf in population do
7:     Calculate fragrance for bf using Eq. (5)
8:     end for
9:     Find the best bf
10:    for each butterfly bf in population do

11:     Generate a random number r from (0, 1)

12:     If r < p then

13:     Move towards best butterfly using Eq. (6)

14:     else

15:     Move randomly using Eq. (7)

16:     end if

17:     end for

18:     Update the value of a

19:     end while

20   Output the best solution found

Figure 3. Algorithm butterfly optimization algorithm.

CASE STUDY

Kuang (1996) used a network consisting of 18 stations, which were observed using the GPS relative positioning technique and 153 baselines. The lengths of the baselines ranged from (2.8) to (36) km, and their total length equaled 2386.87 km, as shown in Fig. (4). The selected GPS receivers assumed that the precision of the baselines (σ_s) could be determined via the following equation (Doma, 2013):

$$\sigma^2{}_s = (2)^2 mm^2 + (1\ ppm.S)^2 \qquad (6)$$

S: the baseline length σ_s: The precision of baselines
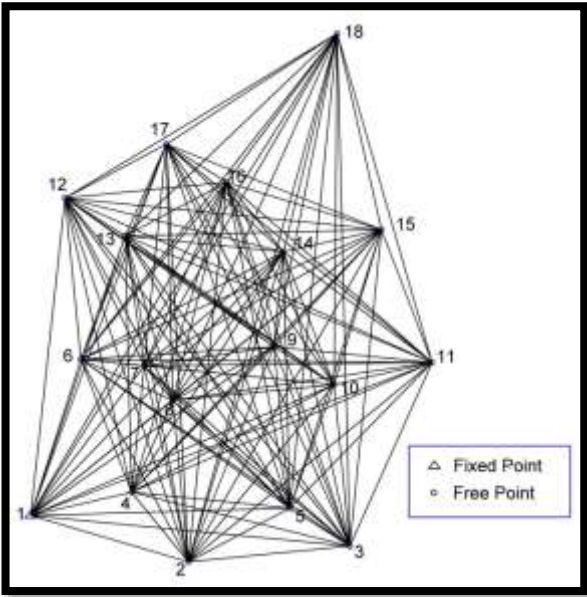

Figure 4. All possible combinations of baselines.

Depending on the proposed configuration of the land, the maximum number of semi-independent baselines is 153. If the measurement of the 153 baselines is observed precisely, as shown in Eq. (6), the standard deviations

of the coordinate elements of every station (given that station (1) is chosen as the fixed datum point) are recorded below (σ_o). In this network, this is the maximum accuracy that can be achieved if all possible baselines are measured. Kuang (1996) suggested that the optimization modeling has been executed using diagonal matrix as its criterion matrix (Doma, 2013):

$$Q_f = diag\{0.0\ 0.0\ 0.0\ \sigma_{2x}^2\sigma_{2y}^2\sigma_{2z}^2 \cdots\cdots \sigma_{18x}^2\sigma_{18y}^2\sigma_{18z}^2\} \qquad (7)$$

where

$$\sigma_{ij}^2 = (\sigma_{oij} + 2.0)^2(mm^2)(i = 2, 3, \ldots\ldots\ldots\ldots, 18; j = x, y, z \qquad (8)$$

σ_{oij} are the minimum possible standard deviations of the coordinate elements of the network stations.

Taking into consideration the maximum achievable weights obtained from the maximum achievable precision expressed by Equation (6), these weights are considered the initial values of observations for the two methods "traditional method (according to Kuang 1996)" and "the proposed method" (BOA method). In Kuang's model (1996), a total of 73 baselines were removed after decreasing the precision of the network by 2.0 mm (saving 47.7 % of the fieldwork). The standard deviations of the station coordinates, as drawn from the optimized observational scheme, are listed under σ_p.

The basic steps for applying the BOA technique to procedure a SOD expressed in equation (2) are given as follows:

1- Determine an initial cofactor matrix (Q_x): from the calculation of P and A matrices, calculate the cofactor matrix expressed in Eq. (1) for all possible baselines.
2- Explain the search area: use the minimum and maximum weights to explain the search area, that is, how butterfly positions are rated at minimum and maximum weights. Minimum weights= 0.0, while maximum weights are determined on the basis of the precision criterion, as explained by Eq. (6).
3- Explain the model of required optimization: determine (Q_f), as explained in Eq. (7).
4- Run (BOA) code: (see the code of MATLAB).

Using the Pc-MATLAB version with a personal computer and the developed mathematical model, this program has been written to calculate the optimal baselines to be selected for GPS survey planning; see Fig. (5).
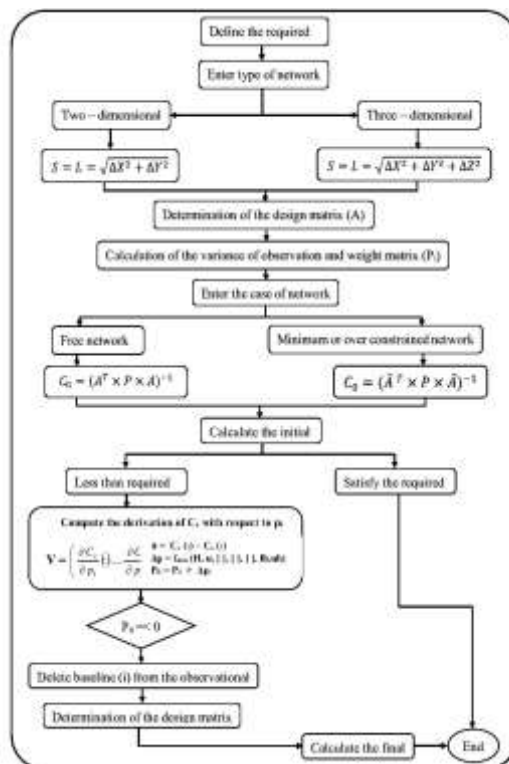
Figure 5. Flowchart of the program.

In the current study, if we allowed for a decrease of 2.0 mm in the precision of the network and used the proposed BOA method to obtain the zero or insignificant weights, a total of 87 baselines should be removed, which means saving 56.9 % of the fieldwork. The standard deviations of the station coordinates, as drawn from the optimized observational chart, are listed under σ_p. Column 13 of Table (1) lists the differences between σ_o and σ_p; all the standard deviations of the coordinate elements obtained from the three methods are less than and close to the required value shown in Figure (6).

Table 1. A comparison of the standard deviations of the coordinates before and after optimization. (using traditional method and artificial method) ("Kuang, 1996", SA, PSO, and BOA method).

| Point	(Kuang, 1996)			(SA method)			(PSO method)			(BOA method)		
	σ_o	σ_P	$\sigma_o - \sigma_P$	σ_o	σ_P	$\sigma_o - \sigma_P$	σ_o	σ_P	$\sigma_o - \sigma_P$	σ_o	σ_P	$\sigma_o - \sigma_P$
1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	4.45	6.34	1.89	4.45	6.46	2.01	4.45	6.43	1.98	4.45	6.13	1.68
3	4.81	6.47	1.66	4.81	6.82	2.01	4.81	6.44	1.63	4.81	6.79	1.98
4	4.01	5.57	1.55	4.01	6.02	2.01	4.01	5.69	1.68	4.01	5.39	1.38
5	4.49	6.31	1.82	4.49	6.50	2.01	4.49	6.04	1.55	4.49	6.46	1.97
6	4.23	5.71	1.48	4.23	6.24	2.01	4.23	5.93	1.70	4.23	6.12	1.89
7	4.06	5.69	1.63	4.06	6.07	2.01	4.06	5.81	1.75	4.06	6.01	1.95
8	4.07	5.90	1.84	4.07	6.08	2.01	4.07	6.00	1.93	4.07	5.98	1.91
9	4.32	6.03	1.71	4.32	6.36	2.01	4.32	6.26	1.94	4.32	5.90	1.58
10	4.44	6.30	1.86	4.44	6.45	2.01	4.44	6.08	1.64	4.44	6.27	1.83
11	4.96	6.97	2.01	4.96	6.98	2.02	4.96	6.96	2.00	4.96	6.96	2.00
12	4.71	6.60	1.88	4.71	6.68	1.97	4.71	6.50	1.80	4.71	6.65	1.94
13	4.44	6.23	1.78	4.44	6.44	2.00	4.44	6.15	1.71	4.44	6.43	1.99
14	4.46	6.26	1.80	4.46	6.54	2.08	4.46	6.23	1.77	4.46	5.73	1.27
15	4.88	6.84	1.96	4.88	6.90	2.02	4.88	6.90	2.02	4.88	6.85	1.97
16	4.53	6.52	1.99	4.53	6.53	2.00	4.53	6.21	1.68	4.53	6.34	1.81
17	4.66	6.52	1.86	4.66	6.70	2.04	4.66	6.30	1.64	4.66	6.48	1.82
18	5.96	7.91	1.95	5.96	7.93	1.97	5.96	7.74	1.78	5.96	7.80	1.84
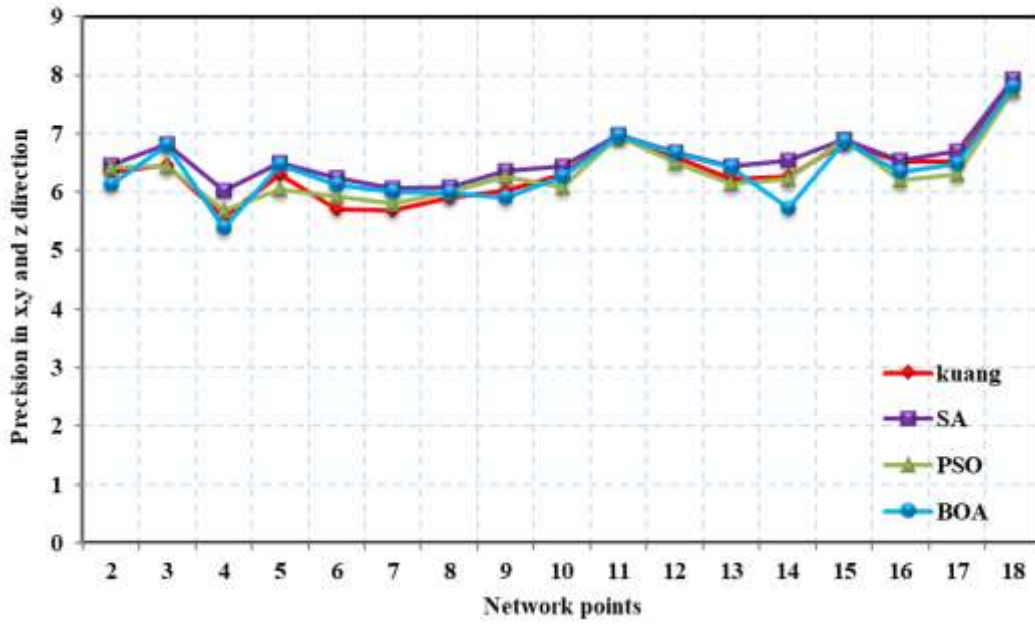
Figure 6. Standard deviations obtained through traditional and artificial intelligence techniques.

Figure (7) shows the optimized observation chart and the total length of the removed baselines equal 1382.85 km, which means saving 57.9% (as shown in Table (2)).
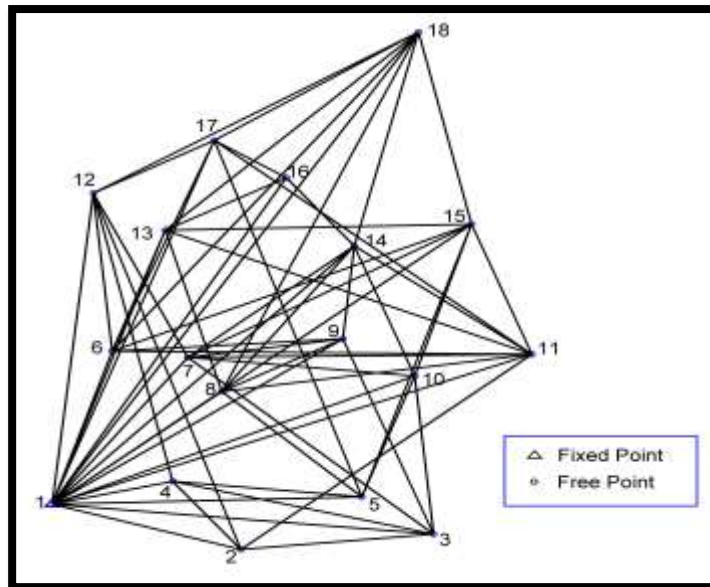

Figure 7. The final baselines after applying (BOA) optimization.

Table 2. The baselines deleted due to optimization (using BOA method).

No.	Baseline		Length (km)	No.	Baseline		Length (km)
	From	To			From	To	
1	2	5	7.213	45	6	7	4.00
2	2	6	14.42	46	6	8	6.324
3	2	7	12.65	47	6	10	16.00
4	2	8	10.20	48	6	14	14.42
5	2	9	14.56	49	6	16	14.42
6	2	10	14.42	50	7	8	2.83
7	2	13	20.88	51	7	13	8.25
8	2	14	20.40	52	7	16	12.65
9	2	15	24.17	53	7	17	14.00
10	2	16	24.00	54	7	18	24.17
11	2	17	26.31	55	8	10	10.20
12	2	18	34.52	56	8	12	14.42
13	3	5	4.472	57	8	15	16.97
14	3	6	20.59	58	8	16	14.14
15	3	8	14.42	59	8	17	16.13
16	3	11	12.65	60	9	10	4.47
17	3	12	28.30	61	9	11	10.00
18	3	13	24.09	62	9	12	16.13
19	3	14	18.97	63	9	13	11.66
20	3	15	20.00	64	9	15	10.00
21	3	16	24.17	65	9	16	10.77
22	3	17	27.79	66	9	17	14.43
23	3	18	32.25	67	9	18	20.10
24	4	6	8.944	68	10	11	6.324
25	4	7	8.00	69	10	12	20.60

26	4	8	6.324	**70**	10	13	16.13
27	4	9	12.81	**71**	10	16	14.42
28	4	10	14.42	**72**	10	17	18.44
29	4	11	20.59	**73**	10	18	22.10
30	4	13	16.12	**74**	11	12	25.30
31	4	14	17.89	**75**	11	16	17.20
32	4	15	22.80	**76**	11	18	21.54
33	4	16	20.39	**77**	12	13	4.474
34	4	17	22.00	**78**	12	14	14.15
35	4	18	31.62	**79**	12	15	20.00
36	5	6	16.13	**80**	12	16	10.20
37	5	7	12.81	**81**	13	14	10.00
38	5	9	10.20	**82**	13	17	6.324
39	5	11	12.81	**83**	14	15	6.324
40	5	12	24.09	**84**	14	17	10.00
41	5	13	20.00	**85**	15	16	10.20
42	5	14	16.13	**86**	15	17	14.56
43	5	16	20.88	**87**	16	18	11.66
44	5	18	30.00	--	--	--	--

DISCUSSION OF RESULTS

We compared the standard deviations before and after optimization among the BOA method and the methods in the previous studies such as the Particle Swarm Optimization (PSO) algorithm, Simulated Annealing (SA) method, and Kuang. It was observed that the standard deviations are more accurate in most baselines in the case of BOA (Fig. 6). Moreover, in the BOA method, after decreasing the precision of the network by (2.00 mm), a total of 87 baselines were removed (saving 56.9% of the fieldwork), while PSO, SA, and Kuang methods saved 56.9%, 51.63%, and 47.7% field work, respectively. The total lengths of removed baselines are 1382.85 Km, 1322 Km, and 1136.33 Km for the methods BOA, PSO, and SA, respectively.

CONCLUSION

This paper aims to shed the light on the importance of new technologies in selecting optimal baselines for GPS networks using the global optimization techniques. We used the Butterfly Optimization Algorithm (BOA) as a new artificial intelligence method for the choice of optimal baselines in GPS networks. The algorithm has been tested on GPS network, which can be solved using the traditional method of Kuang (1996). Our example illustrates that BOA can be adopted effectively to solve complex optimization problems since the number of the baselines removed under the influence of the BOA (87 baselines) was higher than the number of the baselines removed by

the traditional method (73 baselines). Furthermore, the total length of deleted baselines reached 1382.85 km. This result is one of the best results obtained using artificial intelligence methods. The results of this paper were more efficient than those of the traditional method by 19.2%, where they were better than those of the artificial methods in terms of length, and it enhanced the SA method by 21.7% and PSO method by 4.6%. As a result, the use of the BOA is effective and applicable.

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