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USE OF PSO ALGORITHM IN DETERMINATION OF THE OPTIMUM OBSERVATION WEIGHTS IN THE DEFORMATION MONITORING NETWORKS

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ABSTRACT

Geodetic networks are very important tools used to monitor earth and/or structural deformations. However, a geodetic network must be designed to meet sufficiently some network quality requirements such as precision, reliability, or sensitivity. This is the subject of geodetic network optimization. The determination of the observation weights problem in the deformation monitoring networks can be dealt with as an optimization procedure, this problem can performed by solving the second-order design (SOD) problem. Traditional methods have been used for geodetic optimization tasks. On the other hand, some heuristic techniques have been started to be used recently in geodetic science such as the Particle Swarm Optimization (PSO) algorithm. The general purpose optimization method known as Particle Swarm Optimization (PSO) has received much attention in past years, with many attempts to find the variant that performs best on a wide variety of optimization problems.

In this paper, the PSO algorithm, a stochastic global optimization method, has been employed for the determination of the optimum observation weights to be measured in the field that will meet the postulated criterion matrix at a reasonable precision. The fundamentals of the method and a numeric example are given.

مراقبة التشوهات الأرضيه وتشوهات المنشآت واحدة من أهم المهام التي تواجه الجيوديسين وذلك لما لهذه الظاهرة من تأثيرات مباشرة علي أمن وسلامة الإنسان. ولقد ثبت أن الطرق الجيوديسية المصحوبة بأرصاد وتحليلات دقيقة "الشبكات الجيوديسية" من أفضل الطرق المستخدمة لدراسة ومتابعة مثل هذه التشوهات. وتصمم الشبكات الجيوديسية طبقا لمعايير الجوده. ويعتبر تصميم الشبكة مثاليا إذا أمكن تحقيق المعايير السالف ذكرها بأقل التكاليف. وتعتبر أفضل الطرق الرياضية لإيجاد التصيمم الأمثل هي التي تعتمد على تطبيق نظرية الحلول المثلي والتي من خلالها أمكن تحويل عملية التصميم إلي كيفية تعيين الحلول لخمس مسائل. وتعتبر مسألة التصميم الثانية من احدى طرق تصميم الشبكات الجيوديسية ، وهي تبحث في تعيين الأوزان المثلى للأرصاد بافتراض تحديد الدقة المطلوبة وشكل الشبكة. ومع التطور في استخدام طرق الذكاء الإصطناعي مؤخرا في ايجاد الحلول المثلى للمسائل البسيطة والمعقدة أمكن إستخدام مثل هذه الطرق في حل مسائل التصميم المختلفة. وفي هذا البحث استخدمت خوارزمية تحسين أسراب الجسيمات كإحدي طرق الذكاء الصناعي في إيجاد الحل الأمثل لمسألة التصميم الثانية.

1. INTRODUCTION

As with geodetic positioning networks, deformation monitoring network design must precede the field campaign in order to prevent the project from failing. Selection of a monitoring technique depends heavily on the type, the magnitude, and the rate of the deformation. The decision about which instruments should be used and where they should be located leads to the need a proper design and optimization of a proposed measuring scheme that should be based on the best possible combination of all the available measuring instrumentation (Dunnicliff, 1988).

Deformation refers to the changes a deformable body undergoes in its shape, dimension, and position. It can be said that any object, natural or man-made, undergoes changes in space and time.

It has long been a problem to geodesists to find the efficient solutions to approximate functions that define geodetic deformations, especially when dealing with continuously monitored processes (Akyilmaz et all. 2004). In the summery optimization means that determination of maximum or minimum of one target function under of some conditions. For example in the geodetic deformation network, the

target function will be on which represents the network quality i.e. precision, reliability, and cost. This object function should be design in such a way that (Kiamehr, 2003):

- It must be realize the required network quality i.e. precision, reliability, sensitivity, and cost of network and deformation parameters.
- Resistant to gross error in observations and minimize the effects of undetected gross errors.
- It can allow testing of hypothesis with higher significance respect.

Optimization variables are those related to the optimization design problem under consideration.

1. In the **ZOD**, the variables are the datum points, i.e. the coordinates that are to be fixed in the network.
2. In the **FOD**, the configuration matrix that explains the relation of observations with deformation model is the variable (A) as it represents the geometry of the network.
3. The **SOD** defines matrix of observation weights (P) as it's variable.
4. For the **THOD**, the variables are the A-matrix of observations and the P-matrix of their corresponding weights.

Traditional methods have been used for deformation monitoring geodetic optimization tasks. On the other hand, some heuristic techniques such as the particle swarm optimization algorithm or simulated annealing method have been started to be used recently in geodetic science. Optimization and adaptation processes that are encountered in the nature inspire these methods. They are also derivative-free optimization techniques and very promising to solve difficult optimization problems.

Heuristic techniques are used to determine optimal solutions in a reasonable computational time. They are used to solve large-scale problems that cannot be solved optimally and reasonably quickly. However, a heuristic does not guarantee convergence to the global optimal solution. On the other hand, a good heuristic may provide the optimal solution, or at least a solution close to it (Dare and Saleh 2000). The technique is based upon gradually improving an existing solution until the user is satisfied with the quality achieved. The problem with this approach is that the solution is often a local optimum rather than the global optimum. In order to obtain the global optimum it becomes necessary to use global optimization methods. Examples of global optimization methods are Particle Swarm Optimization PSO algorithm and simulated annealing method.

The present study motivates the use PSO algorithm for determining the optimum observation weights (SOD) in the deformation monitoring networks, so the P-matrix will act as the variable.

2. PROBLEM DESCRIPTION

As with geodetic positioning networks, in order to attain the required accuracies of the deformation parameters with an optimal design of the observation weights (Popt.), a properly chosen precision criterion has to be converted into requirements on the unknown parameters to be optimally solved for. In the literature of geodetic network optimal design, optimization means minimizing or maximizing of an objective function that represent the goodness of the network. The goodness of a geodetic network can be measured by precision, reliability and strength, and cost. Only precision criteria is considered in this paper, precision measures of deformation networks are, therefore, based on the variance-covariance matrix of deformation parameters. In the design phase, it is justified to assume that the observation networks are the same for all the epochs. Considering only two epochs, the expressions for the solution of deformation parameters e and their associated variance covariance matrix Ce are as follows (Kuang, 1991; Kuang, 1996).

$$\mathbf{e} = \left(\mathbf{B}^T\mathbf{A}^T\mathbf{P}\ \mathbf{A}\ \mathbf{B}\right)^{-1}\mathbf{B}^T\mathbf{A}^T\mathbf{P}\left(\mathbf{l}_2 - \mathbf{l}_1\right) \quad \text{.....} \quad (1)$$

$$\mathbf{C_e} = \sigma_o^2\,\mathbf{Q_e} = 2\sigma_o^2\left(\mathbf{B}^T\mathbf{A}^T\mathbf{P}\ \mathbf{A}\ \mathbf{B}\right)^{-1} \quad \text{.....} \quad (2)$$

Where:

e: is the vector of unknown deformation parameters.

B: is a deformation matrix with its elements being some selected base functions,

A: is the configuration matrix, which explains the relation of observations with deformation model.

σ_o^2 : Is the priori variance factor that usually taken 1.0 at the design stage.

In the present study, the free networks concept will be used. So, the variance covariance matrix C_e for deformation parameters can be expressed as:

$$\mathbf{C_e} = \sigma_o^2\,\mathbf{Q_e} = 2\sigma_o^2\left(\mathbf{B}^T\mathbf{A}^T\mathbf{P}\ \mathbf{A}\ \mathbf{B}\right)^{+} \quad \text{...} \quad (3)$$

With:

$(\ )^+$: representing the reflexive generalized inverse of a matrix.

Criterion matrices are very adequate tools to set up objective function. Let us consider the case in which a criterion matrix C_e^c for deformation parameters has been chosen as the precision criterion, the design problem then seeks an optimal weights such that it can be best approximated by Ce, i.e., (Kuang, 1991; Yetki et al. 2008).

$$\left\| \mathbf{C_e} - \mathbf{C_e^c} \right\| = \min \quad \text{...} \quad \textbf{(Optimal precision)} \quad (4)$$

And

$$\mathbf{vecdiag}\,(C_e) \le \mathbf{vecdiag}\,(C_e^c) \quad \textbf{(Precision control)(5)}$$

Where: $\|.\|$ represents norm of matrix

Note that elements of matrix Ce are nonlinear functions of the observation weights. When an initial design is given, Taylor series restricted to linear term as follows may approximate matrix Cx:

$$C_e = C_e^o + \sum_{i=1}^{n}\left(\frac{\partial C_e}{\partial p_i}\right)\Delta p_i \quad \ldots\ldots \quad (6)$$

Where:

$$C_e^o = 2\sigma_o^2\left(B^T A^T P\, A\, B\right)^{-1}\Big|_{P^o} \quad \ldots\ldots\ (7)$$

$$\frac{\partial C_e}{\partial p_i} = -\frac{1}{2\sigma_o^2}\left[C_e^o\left(B^T A^T \frac{\partial P}{\partial p_i} A\, B\right)C_e^o\right]_{P^o} \quad \ldots\ (8)$$

So, we can reformulate precision criteria in a compact matrix and vector form (Kung, 1991; Kiamehr, 2003; Doma, 2008). Classic methods have been used for solving this weight problem; these methods that appeared in the literature may cause some problematic cases. Recently, many optimization problems have been solved by using heuristic techniques. These techniques are also named natural optimization methods. Examples of natural optimization techniques are simulated annealing (Kirkpatrick et al., 1983), genetic algorithms (Haupt and Haupt, 2004) and PSO (Parsopoulos and Vrahatis, 2002). These techniques emulate optimization processes encountered in the nature. For example, PSO mimics collective behavior of some creatures such as birds and bees.

3. PARTICLE SWARM OPTIMIZATION (PSO)

The general purpose optimization method known as Particle Swarm Optimization (PSO) is due to Kennedy and Eberhart (1995). PSO, which is an iterative-heuristic search algorithm in swarm intelligence, emulates collective behavior of bird flocking, fish schooling or bee swarming, to converge to the global optimum (Yetki et all. 2011). A basic variant of the PSO algorithm works by having a population (called a swarm) of candidate solutions (called particles). These particles are moved around in the search-space according to a few simple formulae. The movements of the particles are guided by their own best-known position in the search-space as well as the entire swarm's best-known position. When improved positions are being discovered these will then come to guide the movements of the swarm. The process is repeated and by doing so it is hoped, but not guaranteed, that a satisfactory solution will eventually be discovered. Particle swarm optimizers are optimization algorithms, modeled after the social behavior of flocks of birds. PSO is a population based search process where individuals, referred to as particles, are grouped into a swarm. Each particle in the swarm represents a candidate solution to the optimization problem. In a PSO system, each particle is "flown" through the multidimensional search space, adjusting its position in search space according to own experience and that of neighboring particles. A particle therefore makes use of the best position encountered by itself and that of its neighbors to position itself toward an optimal solution. The effect is that particles "fly" towards a minimum, while still searching a wide area around the best solution. The performance of each particle (i.e. the "closeness" of a particle to the global optimum) is measured using a predefined fitness function, which encapsulates the characteristics of the optimization problem. Each particle (i) maintains the following information: xi, the current position of the particle; vi, the current velocity of the particle; and y_i, the personal best position of the particle. The personal best position associated with a particle (i) is the best position that the particle has visited so far, i.e. a position that yielded the highest fitness value for that particle (Kennedy and Eberhart 1995).

The basic PSO algorithm consists of three steps, namely, generating particles' positions and velocities, velocity update, and finally, position update. Here, a particle refers to a point in the design space that changes its position from one move (iteration) to another based on velocity updates. First, the positions, x_k^i, and velocities, v_k^i, of the initial swarm of particles are randomly generated using upper and lower bounds on the design variables values, x_{min} and x_{max}, as expressed in Equations 8 and 9. The positions and velocities are given in a vector format with the superscript and subscript denoting the ith particle at time k. In Equations 8 and 9, rand is a uniformly distributed random variable (Hassan et al. 2004). This initialization process allows the swarm particles to be randomly distributed across the design space.

$$x_o^i = x_{min} + \mathbf{rand}\,(x_{max} - x_{min}) \quad \ldots\ldots \quad (9)$$

$$v_o^i = \frac{x_{min} + \mathbf{rand}\,(x_{max} - x_{min})}{\Delta t} = \frac{\mathbf{position}}{\mathbf{time}} \quad \ldots\ (10)$$

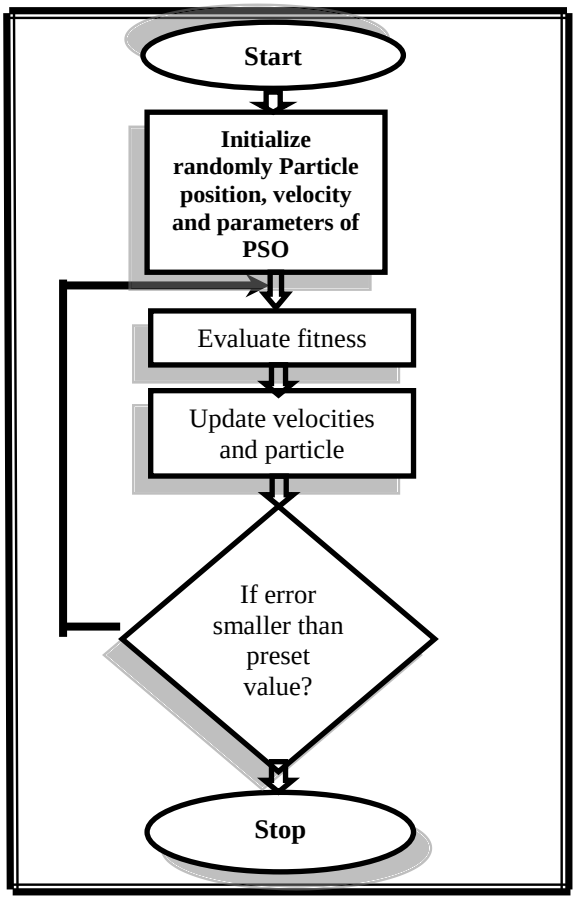

Figure (1): A Particle Swarm Optimization PSO process

The second step is to update the velocities of all particles at time k +1 using the particles objective or fitness values that are functions of the particles current positions in the design space at time k. The fitness function value of a particle determines which particle has the best global value in the current swarm, p_k^g, and also determines the best position of each particle over time, pi , i.e. in current and all previous moves. The velocity update formula uses these two pieces of information for each particle in the swarm along with the effect of current motion, v_k^i, to provide a search direction, v_{k+1}^i, for the next iteration. The velocity update formula includes some random parameters, represented by the uniformly distributed variables, rand, to ensure good coverage of the design space and avoid entrapment in local optima. The three values that effect the new search direction, namely, current motion, particle own memory, and swarm influence, are incorporated via a summation approach as shown in Equation 11 (Hassan et al. 2004).

$$v_{k+1}^i = \underbrace{w\, v_k^i}_{\text{current motion}} + \underbrace{c_1\, \text{rand}\, \frac{(p^i - x_k^i)}{\Delta t}}_{\text{particle memory influence}} + \underbrace{c_2\, \text{rand}\, \frac{(p_k^g - x_k^i)}{\Delta t}}_{\text{swarm influence}} \quad \text{.... (11)}$$

Where: w: inertia factor range 0.4 to 1.4, c1: self-confidences range 1.5 to 2 and c2: swarm confidence range 2 to 2.5.

The original PSO algorithm uses the values of 1, 2 and 2 for w, c1, and c2 respectively, and suggests upper and lower bounds on these values as shown in Equation 10 above. Adjusting these three weight factors w, c1, and c2 provide the best convergence rate (Kennedy and Eberhart, 1995). The tuning of the PSO algorithm weight factors is a topic that warrants proper investigation but is outside the scope of this work. Position update is the last step in each iteration. The Position of each particle is updated using its velocity vector as shown in Equation 11 and depicted in Figure 2.

$$x_{k+1}^i = x_k^i + v_{k+1}^i \Delta t \quad \text{..... (12)}$$

The three steps of velocity update, position update, and fitness calculations are repeated until a desired convergence criterion is met. In the PSO algorithm, the stopping criteria is that the maximum change in best fitness should be smaller than specified tolerance for a specified number of moves, S , as shown in Equation (12).

$$\left| f(p_k^g) - f(p_{k-q}^g) \right| \le \varepsilon \qquad q = 1, 2, \ldots, S \quad \text{.... (13)}$$

In PSO, the design variables can take any values, even outside their side constraints, based on their current position in the design space and the calculated velocity vector. This means that the design variables can go outside their lower or upper limits, x_{min} or x_{max}, which usually happens when the velocity vector grows very rapidly; this phenomenon can lead to divergence. For more detailed information on PSO, interested readers refer to Kennedy and Eberhart (2001), Clerc and Kennedy (2002), Eberhart and Shi (2000) and Parsopoulos and Vrahatis (2002).

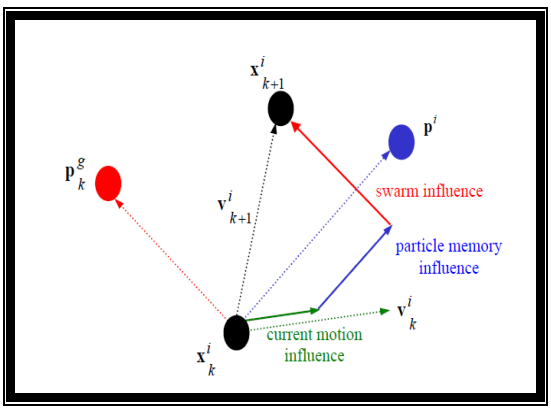

Figure (2): Depiction of the velocity and position updates in PSO

There is much software for PSO technique, Matlab ver. 7.14 (R 2012 a) also has a complete toolbox for PSO. In this paper, the authors designed

some functions to solve the proposed mathematical model (in Equation 5) using PSO method through Matlab software.

4. APPLIED CASE STUDY AND RESULTS

To clarify the applicability of using particle swarm optimization algorithm for determination of the optimum observation weights in the deformation monitoring networks, a numerical example is provided in current study, this example illustrates the application of the proposed approach to the optimal design of a free geodetic network in two-dimensional space using simulated data.

As shown in Figure (3), the network consists of 6 points. The simulated approximate coordinates of all the network points are given in Table (1). The minimum and maximum side lengths of the network are approximately 180.546 m and 657.092 m, respectively. Assume that the deformation model to be detected includes a homogeneous strain field over the whole area plus single point movements of points # 3, # 4 and #5. That is, the vector of deformation parameters to be detected can be expressed as:

$$e = (d_{x_3}\ d_{y_3}\ d_{x_4}\ d_{y_4}\ d_{x_5}\ d_{y_5}\ \varepsilon_x\ \varepsilon_{xy}\ \varepsilon_y)^T \quad \ldots\ldots (14)$$

where dx_i, dy_i (i = 3, 4, 5) represent the displacement of point # 3, # 4 and # 5 in x- and y-directions respectively, $\varepsilon_x, \varepsilon_y$ and ε_{xy} the normal strain and shear strain parameters respectively. The deformation model can be expressed as:

$$\left.\begin{aligned} u_i &= \varepsilon_x x_i + \varepsilon_{xy} y_i \\ v_i &= \varepsilon_{xy} x_i + \varepsilon_y y_i \end{aligned}\right\} \quad \text{for } i = 1, 2, 6 \text{ and } \ldots (14)$$

$$\left.\begin{aligned} u_j &= dx_j + \varepsilon_x x_j + \varepsilon_{xy} y_j \\ v_j &= dy_j + \varepsilon_{xy} x_j + \varepsilon_y y_j \end{aligned}\right\} \quad \text{for } j = 3, 4, 5 \quad \ldots\ldots \quad (15)$$

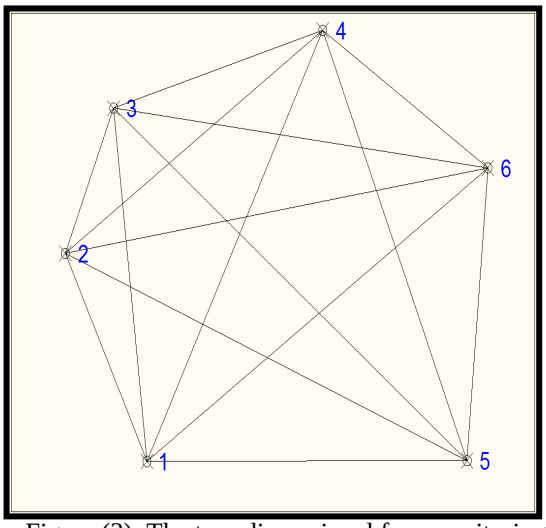

Figure (3): The two-dimensional free monitoring network

Table (1): The simulated approximate coordinates of network points

point	Approximate coordinates	
	X(m)	Y(m)
1	481	576
2	361	814
3	432	980
4	739	1069
5	951	577
6	981	911

Assume that, we can have a choice of an EDM instrument with accuracies ranging from $\sigma_s^2 = (3\text{mm})^2 + (2\,\text{ppm.s})^2$ to $\sigma_s^2 = (1\,\text{ppm.s})^2$, where S is the distance computed from the approximate coordinates. The precision criterion is considered here. A diagonal matrix:

$$C_e = 2.\ \text{Diag}\ [(2\ \text{mm})^2 \ldots (2\ \text{mm})^2\ \ldots\ (5\ \text{ppm})^2] \quad \ldots (16)$$

- For the purpose of simulation study, the following procedure was followed (This case study will be solved for the free network concept):

Step 1: <u>Assumption of an observation scheme and computation of an initial weights</u>. For uncorrelated observations, the initial weights (Pi) for distances are calculated from the EDM accuracy and are listed in table (3).

Step 2: <u>Computation of an initial covariance matrix for deformation parameters</u>: From the simulated coordinates listed in Table (1) and the initial weights of observations, the initial covariance matrix of deformation parameters C_e^o can be expressed by (assuming the variance factor σ_o^2 = 1.0):

$$C_e^o = 2\left(B^T A^T P_i\ A\ B\right)^{+} \quad \ldots\ldots\ldots \quad (17)$$

Note that, from the deformation model "Equations 14 and 15", one can calculate the deformation matrix with its elements being some selected base functions (B), where:

$$\begin{pmatrix} u(x,y,z;t-t_o) \\ v(x,y,z;t-t_o) \end{pmatrix} = \begin{pmatrix} B_u(x,y,z;t-t_o)\ e_u \\ B_v(x,y,z;t-t_o)\ e_v \end{pmatrix} \ldots (18)$$

From the above Equation, one can compute B as:

$$\mathbf{B}=\begin{pmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 481 & 576 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 481 & 576 \\ 0 & 0 & 0 & 0 & 0 & 0 & 361 & 814 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 316 & 814 \\ 1 & 0 & 0 & 0 & 0 & 0 & 432 & 980 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 432 & 980 \\ 0 & 0 & 1 & 0 & 0 & 0 & 739 & 1069 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 739 & 1069 \\ 0 & 0 & 0 & 0 & 1 & 0 & 951 & 577 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 951 & 577 \\ 0 & 0 & 0 & 0 & 0 & 0 & 981 & 911 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 981 & 911 \end{pmatrix}$$

Step 3: Application of PSO method

To test the proposed method "PSO", we assumed that the parameters to be optimized are the weights or standard deviations of all the above proposed observables. These parameters can be obtained by Linear Programming (LP) methods "Kuang, 1991; Kuang, 1996" and are listed in Table (4). Now let us perform optimization for our cost function expressed in Equation (11). PSO algorithms used as a solution strategy and the chosen parameters for PSO are given in table (2). After using the proposed optimization procedure using PSO method by Matlab software, it has satisfied the set precision criteria with sum optimal weights smaller than LP method.

Table (2). PSO parameters

Value	Parameter
30	No. of particles
200	Iteration
1.25	(c_1)
0.5	(c_2)

Table (3): The desired weights of the observations obtained by linear programming (L.P.) method and the proposed method

Obser.		L(m)	P_i	Optimal weights			
				LP method		PSO method	
from	to			P_{opt}	σ_{opt}	P_{opt}	σ_{opt}
1	2	266.54	0.11	0.96	1.02 mm	0.533	1.37 mm
1	3	406.96	0.10	1.86	0.73	0.585	1.31
1	4	556.42	0.10	0.19	2.28	0.501	1.41
1	5	470.00	0.10	0.97	1.02	0.554	1.34
1	6	601.85	0.09	0.82	1.11	0.503	1.41
2	3	180.55	0.11	0.52	1.39	0.509	1.40
2	4	455.97	0.10	0.10	3.14	0.582	1.31
2	5	635.82	0.09	0.85	1.09	0.619	1.27
2	6	627.54	0.09	3.47	0.54	0.465	1.47
3	4	319.64	0.11	2.88	0.59	0.489	1.43
3	5	657.09	0.09	0.09	3.28	0.529	1.38
3	6	553.32	0.10	3.09	0.57	0.638	1.25
4	5	535.73	0.10	0.70	1.20	0.516	1.39
4	6	289.01	0.11	0.11	3.06	0.640	1.25
5	6	335.35	0.11	0.83	1.10	0.563	1.33
Sumations			1.52	17.44	----	8.226	----

Where:
L: is length of side by mater, P_i: the initial weights,
$P_{opt.}$: the optimal weights and
$\sigma_{opt.}$: The standard deviations calculated from the optimal weights

Moreover, as can be seen from Table (3), from the calculated standard deviation of the required observations using the proposed method, one can use an EDM instrument with accuracy $\sigma_s^2 = (2\text{ppm.s})^2$, however from the calculated standard deviation of the required observations using the L.P. method, one can use an EDM instrument with accuracy $\sigma_s^2 = (1\text{ppm.s})^2$. This means that, the PSO method obtains lowest possible cost in comparison with the L.P. method (more accuracy more cost).

Table (4): Goodness of fitting of the precision criteria for both linear programming (L.P.) method and the proposed PSO method.

Parameters	Initial precision	Required precision	Obtained Precision	
			Precision from L.P	Precision from PSO
dx_3	4.76 mm	2.83 mm	1.34 mm	2.13 mm
dy_3	4.58 mm	2.83 mm	1.88 mm	1.85 mm
dx_4	4.40 mm	2.83 mm	1.61 mm	2.00 mm
dy_4	4.85 mm	2.83 mm	2.17 mm	1.99 mm
dx_5	5.36 mm	2.83 mm	1.61 mm	2.37 mm
dy_5	5.14 mm	2.83 mm	1.99 mm	2.01 mm
ε_x	6.51 ppm	5.66 ppm	1.54 ppm	2.88 ppm
ε_{xy}	7.67 ppm	5.66 ppm	2.57 ppm	3.28 ppm
ε_y	12.22 ppm	5.66 ppm	4.53 ppm	4.85 ppm

5. COMMENTS AND CONCLUSIONS

The main goal of the present contribution was to use the Particle Swarm Optimization PSO algorithm in determination of the optimum observation weights in the deformation monitoring networks.

In this paper, we have discussed usage of PSO algorithm in deformation monitoring network. Moreover, the technique performed well in the optimization of deformation monitoring network.

The PSO method can be used for the optimal design of either monitoring schemes, this method can also be easily applied to treat the optimization problems with the mixed models, and the application of the methodology to the optimal design of any deformation monitoring networks for engineering purpose is quite straightforward.

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