A PSO Approach in Solving Staff Transfer Problem

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Abstract

Optimization is ubiquitous, from industry to engineering design, from scheduling your daily routine to your holiday. In many large organizations, from governments to private companies, management of transferring staffs from one location to another plays a major role. The satisfactory assignment of vacant transfer postings to employees is an important issue in Human Resource Management. Optimization of business problems is formerly achieved by using deterministic methods. The objective here is to research and implement a system which gives optimal result and satisfies the employee needs by using Particle Swarm Optimization (PSO), a stochastic meta-heuristics technique. The Staff Transfer Problem is formulated mathematically and applied by the PSO as an application to illustrate its performance. Our experiment gives a perfect result within acceptable time period which cannot be possible by deterministic methods.

Keywords: Staff Transfer Problem, Particle Swarm Optimization, Human Resource Management, Meta-heuristics

1. Introduction

Optimization is everywhere, from business to engineering design, from planning your holiday to your daily routine. Business organizations have to maximize their profit and minimize the cost. Engineering design has to maximize the performance of the designed product while of course minimizing the cost at the same time. Therefore, the studies of optimization are of both scientific interest and practical implications and subsequently the methodology will have many applications [1].

Human resource management is the major subject in every society. Transfers play an important role in human resource flow in organizations, and the satisfactory assignment of transfer postings to employees is an important issue in Human Resource Management [4, 5].

A transfer is a location change in which an employee moves from one office to another. When the transfers involve a large number of employees, it is typically quite difficult to find suitable alternative positions for everyone [2]. Some results have been presented by using modified Simulated Annealing (SA) techniques in [4, 5]. In this study, it is solved by using Particle Swarm Optimization (PSO), a meta-heuristics technique.

PSO is a robust stochastic evolutionary computational technique based on the movement and intelligence of swarms looking for the most fertile feeding location. It is one of the best to find best solution of continuous functions. PSO is based on social-psychological principles and provides insights into social behavior, as well as contributing to engineering applications. PSO is used to find a solution to an optimization problem in a search space, or model and predict social behavior in the presence of objectives [2].

In this paper, using PSO, we propose priority-based assignment where employees are assigned to available vacancies by matching their choices. Priority-based approach decides which employee will be assigned to vacancy the first and who will be the last according to their priority, so that the employee with higher priority values are more likely to get their choices of higher preference.

The rest of this paper is defined as follows. In section 2, we collect some related works. In section 3, we will describe broad understanding of PSO. Section 4 presents problem descriptions and formulation. Section 5 will include implementation and experimental result of our proposed approach. Section 6 will present conclusion of the paper and also discuss about the future works.

2. Related Work

Research in swarm intelligence started in late 1980s and has been attractive to AI researchers because it is simple, robust and offers a new alternative to solve many practical problems [8, 9]. As the name suggests, swarm intelligence models swarms of insects and birds. Through communication, these swarms are able to adjust their behavior and to achieve common objectives. Researchers have used these ideas to solve optimization problems [5, 10, 11, 12, 13, 14, 15].

3. Particle Swarm Optimization

Particle swarm optimization (PSO) is a form of swarm intelligence. A swarm is an apparently disorganized collection of moving individuals that tend to cluster together while each individual seems to be moving in a random direction [2].

Imagine a swarm of birds or insects, or a school of fish. If one sees a desirable path to go (e.g., for food, protection, etc.), the rest of the swarm will be able to follow quickly even if they are on the opposite side of the swarm. On the other hand, in order to facilitate felicitous exploration of the search space, typically one wants to have each particle to have a certain level of "craziness" or randomness in their movement, so that the movement of the swarm has a certain explorative capability: the swarm should be influenced by the rest of the swarm but also should independently explore to a certain extent [2].

3.1. History

Particle Swarm Optimization was developed in 1995 by James Kennedy (social-psychologist) and Russell Eberhart(electrical engineer). The techniques have evolved greatly since then, and the original version of the algorithm is barely recognizable in the current ones. It has roots in the simulation of social behaviors using tools and ideas taken from computer graphics and social psychology research [2].

3.2. Infrastructure

Particle Swarm Optimization is a meta-heuristic (also called global optimization algorithm) for dealing with problems in which a best solution can be represented as a point in an n-dimensional space. PSO is one of the best to find best solution of continuous functions.

Each particle is treated as a point in a N-dimensional space which has a position and a velocity. Each particle adjusts its “flying” according to its own flying experience as well as the flying experience of other particles. Each particle keeps track of its coordinates in the solution space which are associated with the best solution (fitness) that has achieved so far by that particle. This value is called personal best, *pbest*. Another best value that is tracked by the PSO is the best value obtained so far by all the particles in the swarm. This value is called global best, *gbest*. The basic concept of PSO lies in accelerating each particle toward its pbest and the gbest locations, with a random weighted acceleration at each time step as shown in Figure 1.

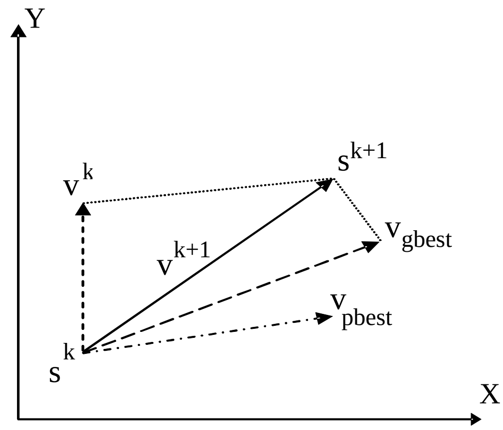
Each particle represents candidate solutions. An iterative process to improve these candidate solutions is set in motion. The swarm moves around in the search space looking for the best solution. The particles iteratively evaluate the fitness of the candidate solutions and accelerate themselves towards pbest and gbest with the population usually converging, by the end of a trial. If particle velocity is too high, it can fly past optimal solutions and if it is too low, then can get stuck in local minima. So, velocity is a sensitive parameter in PSO and therefore should be controlled carefully.

The modification of the particle’s velocity and position in its simplest form can be mathematically modeled according the following equations:

$$V_i(t) = w(t)V_i(t-1)+c_1r_1(X_i^L-X_i(t-1))+c_2r_2(X^G-X_i(t-1)) \quad (1)$$

$$X_i(t) = V_i(t) + X_i(t-1) \quad (2)$$

where particle index i = 1, 2, . . ., M and iteration number t = 1, 2, . . ., T; $X_i^L = \{x_{i1}^L, x_{i2}^L \ldots\ldots x_{iN}^L\}$ represents the local best (position or solution) of the i^{th} particle associated with the best fitness encountered after (t – 1) iterations, while $X^G = \{x_1^G, x_2^G, \ldots; x_N^G\}$ represents the global best among all the population of particles achieved so far. c_1 and c_2 are positive constants (namely acceleration factors) determining the impact of local best position and global best position on current velocity respectively. r_1 and r_2 are random numbers between 0 and 1; w(t) is the inertial coefficient of the velocity, used to control the impact of the previous velocities on the current velocity, influencing the tradeoff between the global and local exploration abilities during search [2].



s^k	:	current searching point.
s^{k+1}	:	modified searching point.
v^k	:	current velocity.
v^{k+1}	:	modified velocity.
v_{pbest}	:	velocity based on pbest
v_{gbest}	:	velocity based on gbest

Figure 1. Concept of modification of a searching point by PSO [2]

3.3. Algorithm

The algorithm begins with the initialization of the swarm in Figure 2. On each iteration, the velocity of each particle is calculated and the position is updated. The PSO will be terminated if the current iteration meets any one of termination signals. The termination signals considered here include:

(1) maximum number of iterations since last updating of the global best, and
(2) maximum total number of iterations.

```
# Swarm Initialization;
foreach particle do
    Initialize particle position;
    Initialize particle velocity;
    Set pBest (Personal Best);
end
Solve for initial gBest (Global Best);
# Swarm Execution:
while iteration count less than limit do
    foreach particle do
        Calculate particle velocity;
        Update particle position;
        if particle fitness is better than pBest then
            Update pBest;
        end
        if particle fitness is better than gBest then
            Update gBest;
        end
    end
end
```

Figure 2. PSO Algorithm [2]

3.4. Parameter selection

A larger inertia weight (w) facilitates global exploration (searching new areas) while a smaller inertia weight tends to facilitate local exploration to fine-tune the current search area. Suitable selection of the inertia weight w can provide a balance between global and local exploration abilities and thus require less iteration on average to find the optimum. Allowing c_1*r_1, $c_2*r_2>1$ permits overshooting and better exploration. There are a number of considerations in using PSO in practice; one might wish to clamp the velocities to a certain maximum amount, for instance. The considerable adaptability of PSO to variations and hybrids is seen as strength over other robust evolutionary optimization mechanisms, such as genetic algorithms. Normally, a stochastic hill-climber risks getting stuck at local maxima, but the stochastic exploration and communication of the swarm overcomes this. Thus, PSO can be seen as a basic search "workbench" that can be adapted as needed for the problem at hand [3].

Clever and proper choices of w, c_i, and r_i will give the optimized results.

4. Problem Description and Formulation

In staff transfer problem, transfer types fall in the following two groups:

- *Lateral Movement:* An employee is transferred to another area or department with the same title, or the same salary range if the title is different.
- *Vertical Movement:* The employee's current position is eliminated due to a restructuring or reclassification and is transferred to a position in a lower salary range. Or the employee will be promoted and is transferred to a position in a higher salary range [6, 7].

4.1. Problem Description

In this study, a transfer is a lateral movement of an employee in an organization, in the same level of hierarchy, requiring similar skills, involving same level of responsibility, same rank and same level of pay. A transfer does not imply any promotion or demotion change in status or rank.

Figure 3 illustrates Staff Transfer Problem in diagram.

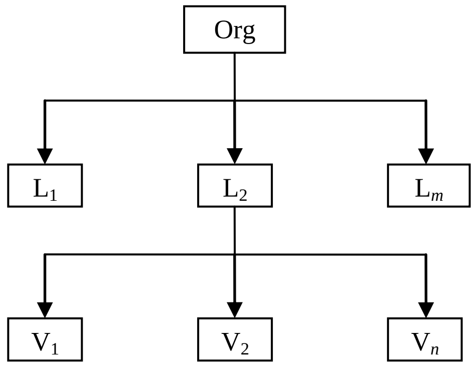


Figure 3. A representation diagram of the Staff Transfer Problem

In an organization Org, there is a set of L locations and a set of V vacancies in each location. The number of vacancies in location 2 (L_2) is *n* and number of locations represents *m*. At any office or branch, the number of vacancies is known. It can be zero, indicating that there is no vacancy currently at that location.

4.2. Formulation for PSO approach

According to Staff Transfer Problem (STP), a staff, who is due for transfer, submits options T according to his preferential locations. The options are arranged by preference, in such a way that the first option has the highest preference, while the second option having the second highest preference and so on. Among T options, a staff should be assigned an option of as high preference as possible [4, 5].

For this study, the option parameter T has a fixed value of 3, describing that each employee gets same opportunity to submit three locations for a transfer, which provides a fair chance to everyone. Each choice of T options has an appropriated cost value, as following:

1. Cost 0 for Choice 1
2. Cost 1 for Choice 2
3. Cost 2 for Choice 3

If any choice in T options does not have a vacancy, it is a "No Match" and the cost will be quite high, here 8. The objective here is to reduce the assignment cost as much as possible, so that the final assignment will meet every staff's choices in their T options.

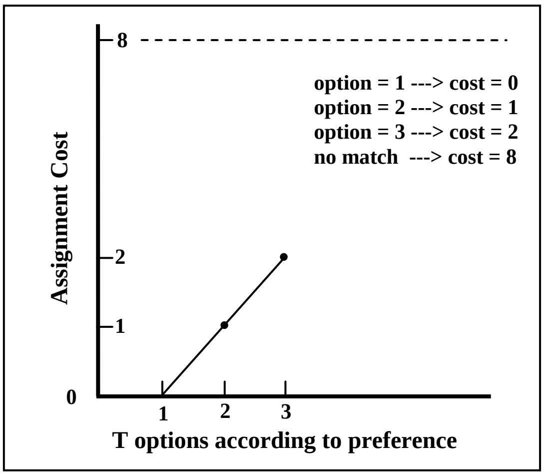


Figure 4. Option-dependent expansion of the assignment cost

The problem is to assign N number of staffs to V number of vacancies in L number of different locations. Here we assume that the number of staffs to be transferred and the number of available vacancies in different locations need to be equal.

$$N = V \qquad (3)$$

For each choice of staff, cost is calculated. If the ith staff is assigned to first choice of location of T options, the assignment cost for that staff will be zero, while the cost having 1 for second choice of location and 2 for the third choice of location respectively. Suppose, if there is no vacancy left for any choice of T options of ith staff, the ith staff is not assigned to any location and the cost will be quite high comparing to the cost of choice in T options, here such cost is 8.

4.2.1. Objective Function

If the cost per choice of i^{th} staff is C_i and the total number of staffs who are to be transferred is *N*, then the total assignment cost is

$$Total\ Cost = \sum_{i=1}^{N} C_i \ , \qquad \forall i \qquad (4)$$

If the cost is high, fitness will be low. The objective is to minimize the cost as much as possible to get the best fitness.

4.2.2. Constraints

Constraints are either strict or desirable. In this study, we assumed that there are one strict constraint and one desirable constraint.

- *SC*: Each of N staffs must be assigned to a location where there is a vacancy.
- *DC*: Among T options, a staff should be assigned an option of as high preference as possible. It can be expressed by the condition:

$$\sum_{i=1}^{N} x_{it} \geq \sum_{i=1}^{N} x_{it+1} \ \text{ for } 1 \leq t < T \qquad (5)$$

where *N* represents number of employees and *T* represents number of staff's options.

5. Realizing PSO approach for STP

In this study, we proposed priority-based assignment where employees are assigned to available vacancies by matching their choices in T options. Priority-based approach decides which employee will be assigned to vacancy first and who will be the last according to their priority, so that the employees with higher priority value are more likely to get their choices of higher preference in T options. But, the priority values will be renewed in every move in the search space, and the best assignment will be replaced by new assignment if new assignment is better than the old one. So, after all moves, the final best assignment with the smallest cost is obtained.

For 25 employees, the size of a particle will be 25, indication that the number of priorities is 25 too. For the next move of particle, the next velocity is calculated according to (1) and the next position is produced by (2).

5.1. Implementation of Staff Transfer System using PSO

In this experiment, there are 25 numbers of staffs (N=25) and 25 numbers of vacancies (V=25) in 10 different locations (L=10). Locations are offices situated in different cities and they are numbered to reference them in coding as shown in Table 1.

Table 1. Cities and their reference numbers

Location No.	Associated City
0	Mumbai
1	New Delhi
2	Kolkata
3	Bangalore
4	Chennai
5	Hyderabad
6	Ahmadabad
7	Pune
8	Surat
9	Kanpur

Table 2. Vacancies in 10 Cities

City	No. of Vacancies
Mumbai	1
New Delhi	3
Kolkata	2
Bangalore	4
Chennai	1
Hyderabad	5
Ahmadabad	4
Pune	2
Surat	1
Kanpur	2
Total no. of vacancies	25

Table 3. Staffs and their choices for a transfer according to preference

Staff No.	Options		
	Choice 1	Choice 2	Choice 3
1	9	5	3
2	8	9	2
3	2	5	3
4	3	0	7
5	9	5	1
6	3	2	8
7	0	7	3
8	9	5	2
9	4	8	6
10	6	9	7
11	4	3	0
12	9	7	2
13	3	7	0
14	0	2	4
15	7	9	5
16	8	0	1
17	3	2	6
18	5	9	8
19	0	8	3
20	9	8	7
21	6	7	1
22	9	5	1
23	0	1	3
24	0	9	5
25	8	9	4

In every location, the number of vacancies is known. It is shown in Table 2. The total number of vacancies in 10 cities must be the same to the number of employees to be transferred, 25 in this system.

Each employee submits T options for a transfer. In this study, the option parameter T has a fixed value of 3. The options are arranged by preference. Table 3 shows staff numbers and their T options, where choice 1 is the highest preference and choice 3 is the lowest preference.

Here, a particle will be a transfer of 25 employees, indication that the number of priorities is 25. For the very first time, 25 priority numbers for 25 staffs are generated randomly between 1 and 999 described in Table 4.

First of all, the employee who has the highest priority number is considered for a transfer. After that it is the turn of next employee with the second highest priority number, and so on. The 3 choices in T options are matched with the vacancies of 10 locations and cost is calculated for each assignment. In every iteration, 25 pbests and one gbest are recorded according to assignment cost. For the next move of particle, the next velocity is calculated by (1) and the next position is produced by (2).

The employees are sorted in decreasing order according to their priority values as shown in Table 5.

Table 4. Staffs with random priorities

Staffs No.	Priority Number
1	750
2	458
3	131
4	250
5	555
6	620
7	604
8	160
9	997
10	648
11	56
12	743
13	248
14	934
15	763
16	433
17	397
18	541
19	797
20	929
21	635
22	336
23	815
24	271
25	926

Table 5. Staffs sorted by priority order

Staff No.	Priority Number
9	997
14	934
20	929
25	926
23	815
19	797
15	763
1	750
12	743
10	648
21	635
6	620
7	604
5	555
18	541
2	458
16	433
17	397
22	336
24	271
4	250
13	248
8	160
3	131
11	56

Since each particle represents candidate solutions, an assignment of 25 vacancies to 25 employees would be one of the potential solutions. The swarm size is the number of particles and the iteration is how many times the swarm will move on the search space. We can adjust swarm size and number of iterations until getting best result. In this study, swarm size is 40, which means there are forty assignments for each iteration. For each assignment, pbest will be produced. There are 40 pbest values for 40 particles. Among pbest, the one with the minimum cost will be chosen as the gbest of that iteration. The gbest after all iterations is the result of the system.

5.1.1. Parameter Selection

The interior weight (w) is set 1. The parameters c_1 and c_2 are 2. It is necessary to make bounds for leading parameter values to prevent the swarm from explosion.

Table 6. Parameters in PSO

Name	Priority Number
w	1
c_1	2
c_2	2
r_1	Random(0,1)
r_2	Random(0,1)
X_{max}	1000
X_{min}	0
V_{max}	10
V_{min}	-10

Each parameter of the initialized or updated position that is beyond [X_{min}, X_{max}] can be adjusted in the following form:

if $x_{ij}(t) > X_{max}$ then $x_{ij}(t) = X_{max}$

else if $x_{ij}(t) < X_{min}$ then $x_{ij}(t) = X_{min}$.

At the same time, the particle velocity based on the current position should also be limited so as to prevent the updated position from oscillating too heavily. Oscillating of the particle velocity may cause particles to fly outside feasible search space (i.e., [X_{min}, X_{max}]) when using (2) and accordingly slow down PSO search. Therefore, the velocity of an updated particle should be limited to [V_{max}, V_{max}]. During PSO search process, each parameter of the N-dimension particle velocity that is beyond [V_{max}, V_{max}] should be adjusted as follows:

if $v_{ij}(t) > V_{max}$ then $v_{ij}(t) = V_{max}$

else if $v_{ij}(t) < V_{min}$ then $v_{ij}(t) = V_{min}$.

In our experiments V_{max}= 10 and V_{min}= -10.

The inertia weight w(t) can be constant or varying with iteration. Varying inertia weight (i.e., from larger to smaller) is recommended to enhance global exploration for early iterations and to facilitate local exploration for late iterations. In our solution we have taken w(t)=1 as it is found the best suitable value for the problem under consideration. Generally inertia weight of 1 is a good choice when the maximum velocity is small.

For the number of particles in the population or swarm, called swarm size, more particles may increase success in searching for optima due to sampling state space more thoroughly. However, more particles require more evaluation runs, leading more optimization cost. Therefore, a medium number of particles are generally selected for the PSO-based approach. The difference caused by different learning factors c_1 and c_2 is not obvious; hence, they are set to 2 as usual.

5.2. Experimental Observation

Here, a particle will be a transfer of 25 employees, indication that the number of priorities is 25. For the very first time, 25 priority numbers for 25 staffs are generated randomly between 1 and 999.

Table 7. Experimental result of gbest Assignment

Staff No	Assigned Location No	Associated City	Options	Cost
1	5	Hyderabad	Choice 2	1
2	8	Surat	Choice 1	0
3	2	Kolkata	Choice 1	0
4	3	Bangalore	Choice 1	0
5	1	New Delhi	Choice 3	2
6	3	Bangalore	Choice 1	0
7	7	Pune	Choice 2	1
8	5	Hyderabad	Choice 2	1
9	6	Ahmadabad	Choice 3	2
10	6	Ahmadabad	Choice 1	0
11	3	Bangalore	Choice 2	1
12	9	Kanpur	Choice 1	0
13	3	Bangalore	Choice 1	0
14	2	Kolkata	Choice 2	1
15	7	Pune	Choice1	0
16	1	New Delhi	Choice 3	2
17	6	Ahmadabad	Choice 3	2
18	5	Hyderabad	Choice 1	0
19	0	Mumbai	Choice 1	0
20	9	Kanpur	Choice 1	0
21	6	Ahmadabad	Choice 1	0
22	5	Hyderabad	Choice 2	1
23	1	New Delhi	Choice 2	1
24	5	Hyderabad	Choice 3	2
25	4	Chennai	Choice 3	2
gbest Cost				**19**

We set the parameters $c_1 = c_2 = 2$; w is gradually decreased from 1 towards 0.1. Some variants of PSO, impose a maximum value on the velocity, V_{max}, to prevent the swarm from explosion. In our experiments, we assumed that $V_{max} = 10$ and $V_{min} = -10$. Also we set the size of the swarm as 40 with 500 iterations in each run.

After several runs by adjusting leading parameters, the excellent parameters which produced the best results were found. These parameters are $c_1 = c_2 = 2$ and w = 0.7. The program takes about 15 seconds for each run. Among 10 results after the last 10 runs using the above parameter values, the result with cost 19 is the best. The costs are between 19 and 23; mostly 20 and 21. The result which is the assignment with minimum cost is shown in Table 7.

When we run by adjusting swarm size less than or greater than 40, it is found that the result is with more unassigned number of staffs to transfer locations or higher average cost, which is shown in Table 8.

Table 8. Experimental result by adjusting swarm size

Swarm Size	Average Cost	Maximum Number of Unassigned Staffs to Locations
<40	21	2
>40	21	1
~=40	20	1

From our experiments, by setting swarm size 40, we found the feasible solution that the program ever generates. Table 7 illustrates the result of gbest assignment with minimum cost(gbest =19), that is, our proposed objective function depicted in (4) has been achieved. The result shows that the system could successfully assign all employees to their preference locations in their T options while all constraints depicted in article 4.2.2 have been satisfied.

In this work, optimization describes a situation where all staffs are assigned to their prefer locations as high as possible. Thus, the result in Table 7 yields the optimized solution with cost 19 while all staffs have been assigned to their higher preferred locations.

6. Conclusion and Future Work

In this paper, Staff Transfer Problem is assumed as an optimization problem and it has been solved by using PSO approach while satisfying some constraints as well. We discovered that complex Staff Transfer Problem could have been handled by PSO with excellent results without consuming much time.

We focused on the transfers of employees who are under one category of ranks and job types. We assumed that the number of employees, who are to be transferred, equals to the number of vacancies in different locations. As a future work, the problem under various ranks and job types and the condition where number of employees and number of vacancies are different should be studied.

In this paper, basic PSO for single objective has been studied. In further extension, to apply PSO on multi-objective optimization problems, Multi Objective PSO (MOPSO) which is an extended version of basic PSO should be studied. The problem under consideration should be formulated in a manner so that the Multi Objective PSO approach can be applied on the problem.

Other meta-heuristic approaches like Genetic Algorithm can also be applied on the problem under consideration as GA is also able to find optimum solution for multi-objective optimization problems.

Then a comparative analysis can be done based on the performance of these two meta-heuristics.

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