Paper 27

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A Particle Swarm Optimization for Employee Placement Problems in the Competency Based Human Resource Management

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ABSTRACT
This paper discussed on how particle swarm optimization could be applied for solving the employee placement problems in the competency based human resource management. The employee placement problems are the problems to simultaneously place many people to many jobs in an organization. After the particle swarm mechanism to solve the problem is defined and explained, simple case study is presented to illustrate the capability of the proposed method.

KEYWORDS
Employee placement problem; Human resource management; Competency based human resource management; Particle swarm optimization; Evolutionary computing.

I. INTRODUCTION
Competency Based Human Resource Management (CBHRM) is a process to manage people optimally in organization from recruitment, selection, placement up to termination process based on job competency profiles and individual competencies in order to achieve organization goals, missions and vision [1]. One of CBHRM function is placement. It is a process to put the right persons at the right places at the right time which is very critical for the success of any modern organizations.

Usually, a placement problem involves a multi criteria decision making process. At a simplest case, an employee can be rotated or promoted to a certain job within an organization one by one sequentially based on a set of criteria of past performance, current competencies and future expectations. But sometimes, in more complex problem, organization needs to place many people to many jobs, even for the whole organization, simultaneously. This paper will demonstrate the application of Particle Swarm Optimization (PSO) to find best methods for these employee placement problems.

PSO is a population based search method proposed by Kennedy and Eberhart [2], which were motivated by the group organism behavior such as bee swarm, fish school, and bird flock. PSO imitated the physical movements of the individuals in the swarm as a searching method, altogether with its cognitive and social behavior as local and global exploration abilities. One of PSO advantage is its simplicity of its iteration step which only consists of updating two set of equations. PSO is widely used as a solution methodology for solving numerous combinatorial optimization problem such as job shop scheduling [3], vehicle routing [4], and project scheduling [5].

Due to its simplicity and unexplored potential in the HRM area, this paper will discuss on how particle swarm optimization could be applied for solving the employee placement problems in the CBHRM. Specifically, it will describe on how the solution of the problem, which is the placement of the employees, could be represented as a multi-dimensional particle. Also, the decoding method for translating particle into employee placement is also explained.

Simple case study will be presented at the end of this paper to illustrate the capability of the proposed particle swarm optimization algorithm for solving the employee placement problem. The advantages and disadvantages of this algorithm will also be discussed further, altogether with its opportunity for improvement and extension.

II. EMPLOYEE PLACEMENT PROBLEM

A. Problem Definition

The employee placement problem (EPP) in an organization can be defined as the problem to place many employees to many jobs simultaneously based on a set of criteria of past performance, current competencies and future expectations.

Regarding to the competencies criterion, the employees' competencies should be aligned with the job competency profile. The job competency profiles provide a list of competencies and the minimal scores on those competencies required to hold the jobs, while the employees' competencies are the quantitative score of each employee on those competencies. The minimal score on a competency is the quantification of capability required on the competency. Therefore, employee with lower scores than minimal required scores of a certain job position is not qualified to hold that job. [6] For the placement criteria, the closeness among employee's competencies and job competency profiles is the measurement basis of the competency performance score of an employee on a particular job.

The generic EPP could be defined as the problem to place a set of employee consisting of m potential people into a set of n available jobs in order to maximize the total weighted score of the criteria, subject to the required competencies. In this generic definition, it is assumed that a job can be filled at most by a single employee.

Each criterion may comprised of many sub-criteria, that is could be defined in hierarchical form. For example the competency criterion can be divided into major competency, supporting competency, and field competency; whereas the major competency is comprised of five sub-competencies. Using a proper methodology, such as the analytic hierarchy process (AHP), the weights of each competency and sub-competency can be determined. In the mathematical formulation defined below, these weights are utilized for obtaining the total weighted score of the criteria as the objective function of the decision problem.

B. Mathematical Formulation

The EPP can be formulated as the following integer programming problem:

$$\text{Maximize } Z = \sum_{i=1}^{m}\sum_{j=1}^{n}\left[\left(\alpha_i + \beta_{ij} + \gamma_{ij}\right)\cdot x_{ij}\right] \qquad (1)$$

Subject to

$$\sum_{i=1}^{m} x_{ij} \le 1, \text{ for } \forall j \qquad (2)$$

$$\sum_{j=1}^{n} x_{ij} \le 1, \text{ for } \forall i \qquad (3)$$

$$x_{ij} = 0, \text{ for employee } i \text{ that is not qualified to hold job } j \qquad (4)$$

$$x_{ij} \in \{0,1\}, \text{ for } \forall i,\ \forall j \qquad (5)$$

where:

- m : number of potential employees
- n : number of available jobs
- x_{ij} : binary assignment variable, $x_{ij} = 1$ if employee i assigned to job j, $x_{ij} = 0$ otherwise
- i : index of employee, $i = 1 \ldots m$
- j : index of job, $j = 1 \ldots n$
- α_i : past performance score of employee i
- β_{ij} : current competency performance score of employee i on job j
- γ_{ij} : future expectation score of employee i on job j

The objective function in Eq. 1 is showing that the higher the past performance of an employee, the bigger chance the employee being placed in any jobs. Also, it is implied that the employee placement tends to place an employee in a job that is maximizing the current competency performance and the future expectation scores in all jobs.

Eq. 2 states that all job to be fulfilled by at most one employee. Whenever no employee is qualified to hold a job, it is not necessary to place any employee to that job. Eq. 3 shows that one employee is placed at most to one job. In the Eq. 4, the binary assignment variables are limited by employees' qualification on the available jobs. The variables domain is defined in the Eq. 5.

In nature, the mathematical formulation of EPP has $m \cdot n$ binary variables. Therefore, if the EPP is being solved using total enumeration technique, it has $2^{m \cdot n}$ alternative solutions that should be evaluated.

III. DATA PREPROCESSING

There are three steps of preprocessing the human resource data into parameters required in the EPP: job and employee sets definition, CBHRM data extraction, and criteria evaluation.

A. Job and Employee Sets Definition

In the first step, the number of available jobs is identified. For the job with many available positions, every position is defined as different job so that each job can be fulfill only by single employee. The job ID is assigned based on its importance or rank, i.e. the first job (j=1) is the most important job or the highest-rank job and the last job (j=n) is the least important job or the lowest-rank job.

After the job set is defined, the employee set is defined, i.e. by listing the candidates that are possible to be placed at least one job in the job set.

B. CBHRM Data Extraction

In this step, the CBHRM data is extracted to find the job competency profiles for each job in the job set, past performances of each employee in the employee set, current competency performances of employees, and future expectations of employee placed into particular job.

C. Criteria Evaluation

Using the AHP method, the particular CBHRM data is being processed into the score criteria: the past performance score of employee i (a_i), the current competency performance score of employee i on job j (β_{ij}), and the future expectation score of employee i on job j (γ_{ij}). At the end of this step, all parameters required in the EPP are available so that the EPP is ready to be solved.

IV. PSO METHOD FOR SOLVING EPP

A. PSO Algorithm [7]

As mentioned before, PSO is a population based search method that imitated the physical movements of the individuals in the swarm as a searching method. In PSO, a swarm of L particles served as searching agent for a specific problem solution. A particle's position (Θ_l), which consists of H dimensions, is representing a solution of the problem. The ability of a particle to search for solution is represented by its velocity vector (Ω_l) which drives particle movement. In the PSO iteration step, every particle moves from one position to the next based on its velocity. Moving from one position to another, a particle is evaluating different prospective solution of the problem. The basic particle movement equation is presented below:

$$\theta_{lh}(\tau+1) = \theta_{lh}(\tau) + \omega_{lh}(\tau+1) \tag{6}$$

where:

$\theta_{lh}(\tau+1)$: Position of the l^{th} particle at the h^{th} dimension in the $(\tau+1)^{th}$ iteration

$\theta_{lh}(\tau)$: Position of the l^{th} particle at the h^{th} dimension in the τ^{th} iteration

$\omega_{lh}(\tau+1)$: Velocity of the l^{th} particle at the h^{th} dimension in the $(\tau+1)^{th}$ iteration

PSO also imitated swarm's cognitive and social behavior as local and global search abilities. In the basic version of PSO, the particle's personal best position (Ψ_l) and the global best position (Ψ_g) are always updated and maintained. The personal best position of a particle, which expresses the cognitive behavior, is defined as the position that gives the best objective function among the positions that have been visited by the particle. Once a particle reaches a position that has a better objective function than the previous best objective function for this particle, i.e. $Z(\Theta_l) < Z(\Psi_l)$, the personal best position is updated. The global best position, which expresses the social behavior, is the position that gives the best objective function among the positions that have been visited by all particles in the swarm. Once a particle reaches a position that has a better objective function than the previous best objective function for whole swarm, i.e. $Z(\Psi_l) < Z(\Psi_g)$, the global best position is also updated.

The personal best and global best position are used for updating particle velocity. In each iteration step, the velocity Ω is updated based on three terms: inertia, cognitive learning and social learning terms. The inertia term forces particle to move in the same direction as previous iteration. This term is calculated as a product of current velocity with an inertia weight (w). The cognitive term forces particle to go back to its personal best position. This term is calculated as a product of a random number (u), personal best acceleration constant (c_p), and the difference between personal best position Ψ_l and current position Θ_l. The social term forces particle to move to the global best position. This term is calculated as a product of a random number (u), global best acceleration constant (c_g), and the difference between global best position Ψ_g and current position Θ_l. To be more specific, the velocity updating equation is expressed as follow:

$$\omega_{lh}(\tau+1) = w\omega_{lh}(\tau) + c_p u(\psi_{lh} - \theta_{lh}(\tau)) + c_g u(\psi_{gh} - \theta_{lh}(\tau)) \quad (7)$$

where:

$\omega_{lh}(\tau)$	:	Velocity of the l^{th} particle at the h^{th} dimension in the τ^{th} iteration
ψ_{lh}	:	Personal best position of the l^{th} particle at the h^{th} dimension in the τ^{th} iteration
ψ_{gh}	:	Global Personal best position at the h^{th} dimension in the τ^{th} iteration

In the velocity-updating formula, random numbers is incorporated in order to randomize particle movement. Hence, two different particles may move to different position in the subsequent iteration even though they have similar position, personal best, and global best.

Algorithm 1: Basic PSO Algorithm

Step 1: Initialization

- Set the PSO parameters: T, L, w, c_p, c_g.
- Set the iteration counter, $\tau = 1$.
- Generate L particles with random initial position (Θ_l) and zero velocity ($\Omega_l = 0$).
- Set the initial personal best position the same as its position ($\Psi_l = \Theta_l$).

Step 2: Iteration – Particles Movement

- Decode each particle into a problem specific solution and evaluate the objective function of the solution. Set the objective function value as the fitness value of the particle $Z(\Theta_l)$.
- Update the personal best position of each particle, set $\Psi_l = \Theta_l$ if $Z(\Theta_l) < Z(\Psi_l)$.
- Update the global best position, set $\Psi_g = \Psi_l$ if $Z(\Psi_l) < Z(\Psi_g)$.
- Move each particle based on Eq. 6, after updating particle velocity based on Eq. 7.

Step 3: Termination

- If the terminating criterion is reached, i.e. $\tau = T$, the stop the iteration. The solution corresponding with the last global best position is the best solution found by this algorithm.
- Otherwise, set the iteration counter $\tau = \tau + 1$, and back to Step 2.

B. Solution Representation

In the PSO, a problem specific solution is represented by position of particle in multi-dimensional space. The proposed solution representation of EPP with m employees and n jobs is a m dimensional particle. Each particle dimension is encoded as a real number. These m dimensions are related to employees, in which each employee is represented by one dimension. The position value in each particle dimension will be represented the priority weight of its corresponding employee to be placed into jobs in the decoding steps.

Dimension 1	1.075
Dimension 2	0.344
Dimension 3	3.150
Dimension 4	4.593
Dimension 5	2.728

Figure 1. A Solution Representation of EPP (m=5)

C. Decoding Method

The decoding method is required to transform a particle (represented by its position) into a problem specific solution, which is the placement of employees into jobs in the EPP.

As mentioned before, the first step in the decoding method is the extraction of employee priority weight from the position value. Each employee will be given a priority weight from its corresponding particle dimension. For example, the particle depicted on Fig. 1 can be transformed into following priority weight for five employees: 1.075, 0.344, 3.150, 4.593, 2.728.

It is defined that the priority of an employee to be placed into jobs is correspond to its priority weight. Therefore, employee with higher priority weight will be given more priority than employee with lower priority weight. So, continuing the example, the fourth employee will be given the first priority and finally the second employee will be given the last priority. The complete information related to employee priority could be kept into a list illustrated in Table 1.

Table 1. An Employee Priority List

Employee ID	Priority Weight	Priority Rank
4	4.593	1
3	3.150	2
5	2.728	3
1	1.075	4
2	0.344	5

After the employee priority list is created, the placement of employee into job is performed. One by one each employee in the employee priority list, starting from the first rank, is placed into a job considering the rank of job, availability of job, and employee's qualification. An employee will be placed at the highest rank job that is matched with employee qualification and has not assigned to other employee yet. It is possible to have a situation where is no more available job for an employee. Finally, the total employee placement could be conducted and the result could be displayed as illustrated in Table 2.

Table 2. An Employee Placement

Employee ID	Job ID
4	2
3	–
5	1
1	3
2	–

It is implied from the example illustrated in Table 2, that the fourth employee is not qualified for the first job so that this employee is assigned to the second job. Also, the third employee is qualified only for the second job. Since the second job is already assigned to the fourth employee, this employee could not be placed at any job. The fifth employee is qualified for the first job and the first employee is met the qualification of the third job. Therefore, no more job available for the second employee.

V. CASE STUDY

A simple case study is conducted to illustrate the capability of the proposed particle swarm optimization algorithm for solving the employee placement problem. The case comprises of a problem to place five employees into three available jobs. Hypothetical CBHRM data is used here, which consists of job competency profiles, past performances of each employee, current competency performances of employees and future expectations of employee placed into particular job.

To test the performance of the proposed PSO, the algorithm is coded into computer program using C# language. PSO parameters used to solve this case are: number of particle $L = 30$, number of iteration $T = 200$, decreasing inertia weight w from 0.9 to 0.4, personal best acceleration constant $c_p = 2$, and global best acceleration constant $c_g = 2$. Since the PSO has random property, five replication of the algorithm is run.

For comparison purpose, total enumeration of possible solutions is performed. All possible solutions are evaluated, so that the best employee placement can be determined. Among the five PSO replications performed, three replications provide the same result as the best employee placement and the other replications provide a solution which its objective function is very close with the objective function of the best employee placement.

VI. CONCLUSIONS AND FURTHER WORKS

The simple case study above shows that the proposed solution representation and decoding method are effective for solving the EPP using basic PSO. The effectiveness of this method is still need to be confirmed using larger sized and real-world problem.

It is noted that the result on this paper is gained by pure PSO algorithm. Hence, it is possible to improve the result by more sophisticated PSO variants and features. Also, it is possible to hybridize this PSO with other technique, i.e. local search method. It is also possible to improve the performance of the proposed algorithm by parameter optimization and programming implementation.

Integrating this EPP solving module inside the CBHRM system, including automated data extraction, is the ultimate direction of this research.

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Paper 27

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