.Particle Swarm Optimization in Emergency Services

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ABSTRACT:

Particle Swarm Optimization (PSO) is motivated by the social behaviour of organisms, such as bird flocking and fish schooling. Each particle studies its own previous best solution to the optimization problem, and its group's previous best, and then adjusts its position (solution) accordingly. The optimal value will be found by repeating this process. PSO can be useful in different applications. PSO can be used in Multi Modal Optimization (MMO), Multi Objective Optimization (MOO) and Vehicle Routing Problems (VRP). This paper presents a solution representation and the corresponding decoding method for solving the emergency services problems using PSO. PSO algorithm can be used to solve the emergency problem, because different and outspread solutions can be generated in PSO. It means that the generated solutions by particles spread in entire search space of the problem. PSO algorithm can also keep the best solution until the iteration stops. The solution representation is a p-dimensional particle for emergency services with p injured. The decoding method for this representation starts with the transformation of particles into a priority list of p injured to allocate an ambulance and a hospital to each injured according to the constraints of the problem. For assigning each ambulance to each injured, time is considered as a constraint. Also assigning hospitals to the injured is done according to hospital's capacity. The proposed solution is applied using PSO algorithm with star topology, and tested on a small district in Tehran Metropolitan Area (TMA).

1. INTRODUCTION

PSO can be used in multimodal optimization and multiobjective optimization problems (VRP) (Alexander and Darrell, 2006; Carlos et al; Fernandes and Ismael, 2005). Also different applications like Vehicle Routing Problems (VRP) can use PSO algorithm (Jung, Haghani, 2005; Wanliang and Yanwei, 2006). The Emergency Services problem is a problem to design a set of ambulance routes in which a fixed fleet of ambulances with same capacity must service known injured demands for an ambulance from an emergency center and carry them to specified hospital at minimum cost. Set of p injured requires a number of ambulances from an emergency center. A fleet of n identical ambulances with same capacity is stationed at the emergency center. The emergency center, injured and hospital locations are known; the travel distance or travel costs between locations are also known. The distances between locations are calculated by Dijkstra algorithm. The speed of ambulances is assumed to be constant during the trip. Therefore, the travel time between locations can be calculated. This problem consists of designing a set of at most n routes such that (1) each route starts at the emergency center and ends at the specified hospital, (2) each injured is carried to the nearest hospital according to the hospitals capacity, (3) each injured is serviced by an ambulance in shortest possible time, (4) the total routing cost is minimized.

Studying the emergency services problem and its method for finding solution of the problem is necessary to protect the health and safety of the injured people. It is known that this problem is an NP-hard problem, in which finding the optimal solution is very hard and requires very long computational time.

PSO is an optimization technique which first developed by James Kennedy (social psychologist) and Russell Eberhart (electrical engineer) in 1995 (Kennedy and Eberhart, 1995). In PSO, individuals, referred to as particles, are "flown" through hyperdimensional search space. Changes to the position of particles within the search space are based on the social-psychological tendency of individuals to emulate the success of other individuals. The changes to a particle within the swarm are therefore influenced by the experience, or knowledge, of its neighbours. The search behaviour of a particle is thus affected by that of other particles within the swarm. The consequence of modelling this social behaviour is that the search process is such that particles stochastically return toward previously successful regions in the search space (Engelbrecht, 2007).

Each particle has the following properties:

- Each agent was attracted towards the location of the roost (Engelbrecht, 2007).
- Each agent 'remembered' where it was closer to the roost (Engelbrecht, 2007).
- Each agent shared information with its neighbors (originally, all other agents) about its closest location to the roost (Engelbrecht, 2007).

The research on the application of PSO to emergency services is a new subject which is focused on this paper.

In order to make PSO applicable to emergency services, the relationship between particle position and ambulance routes must be clearly defined. The definition of particle as an encoded solution is usually called a solution representation and the method to convert it to problem specific solution is usually called a decoding method (Jin and Voratas, 2008). This paper proposes a solution representation and its corresponding decoding method to convert position in PSO into emergency services solution. This solution representation is a new proposed representation which is an extension of the work of Ai and Kachitvichyanukul (Jin and Voratas, 2008).

The reminder of this paper is organized as follow: Section 2 reviews PSO framework for solving emergency services. Section 3 explains the proposed solution representation and decoding method. Section 4 is computational result and finally, section 5 summarizes the result of this study and suggests further directions in this research.

2. PSO FRAMEWORK FOR SOLVING THE EMERGENCY SERVICES

The PSO framework for solving emergency services is based on gbest PSO, an algorithm with star topology (Marco and Montes, 2007). This algorithm is designed for the minimization problem, since the emergency services problem is to minimize total route cost and allocating nearest ambulance and hospital to each injured according to the constraints.
The notation and the description of the algorithm are given as follows (Voratas, 2007).

Notation
$\boldsymbol{t}$ $Iteration\ index, t = 1,2,\dots,T$
$\boldsymbol{i}$ $Particle\ Index, i = 1,2,\dots,I$
$\boldsymbol{d}$ $Dimension\ index, d = 1,2,\dots,D$
$\boldsymbol{u}$ $Uniform\ random\ number\ in\ the\ Interval$ [0,1]
$\boldsymbol{v_{id}(t)}$ Velocity of the ith particle at the dth dimension in the tth iteration
$\boldsymbol{X_{id}(t)}$ Position of the ith particle at the dth dimension in the tth iteration
$\boldsymbol{P_{id}}$ Personal best position (pbest)of the ith particle at the dth dimension
$\boldsymbol{P_{gd}}$ Global best position (gbest) at the dth dimension
$\boldsymbol{w(t)}$ Inertia weight in the tth iteration
$\boldsymbol{c_p}$ Personal best position acceleration constant
$\boldsymbol{c_g}$ Global best position acceleration constant
$\boldsymbol{X_i}$ Vector position of ith particle, $[x_{i1}, x_{i2}, \dots, x_{iD}]$
$\boldsymbol{V_i}$ Vector velocity of ith particle, $[v_{i1}, v_{i2}, \dots, v_{iD}]$
$\boldsymbol{P_i}$ Vector personal best position of ith particle, $[P_{i1}, P_{i2}, \dots, P_{iD}]$
$\boldsymbol{P_g}$ Vector global best position, $[P_{g1}, P_{g2}, \dots, P_{gD}]$
$\boldsymbol{f(X_i)}$ Fitness value of X_i
$\boldsymbol{X^{min}}$ Minimum position value
$\boldsymbol{X^{max}}$ Maximum position value

1. Initialize I particles as a population, generate the ith particle with random position X_i in the range $\left[X^{min}, X^{max}\right]$ and initial velocity $V_i = 0$ and pbest $P_i = X_i\ for\ i = 1,2,\dots,I,\ \ iteration\ t = 1.$
2. $for\ i = 1,2,\dots,I, decode\ X_i\ \ to\ a\ set\ of\ specified\ ambulance\ and\ hospital\ that\ is\ assigned\ to\ each\ injured$
3. $for\ i = 1,2,\dots,I, compute\ the\ fitness\ of\ particles$
4. $update\ pbest\ for\ i = 1,2,\dots,I, update\ P_i = X_i\ if\ f(X_i) < f(P_i)$
5. $update\ gbest\ for\ i = 1,2,\dots,I, update\ P_g = P_i\ if\ f(P_i) < f(P_g)$
6. $update\ the\ velocity\ and\ the\ position\ of\ each\ particle\ as$

$$\begin{aligned} v_{id}(t+1) &= w(t)v_{id}(t) + c_p u\big(P_{id} - X_{id}(t)\big) \\ &+ c_g u\left(P_{gd} - X_{id}(t)\right) \end{aligned}$$

$$X_{id}(t+1) = X_{id}(t) + v_{id}(t+1)$$

$$X_{id}(t+1) > X^{mzx}$$
$$\Rightarrow x_{id}(t+1) = X^{\max}, v_{id}(t+1) = 0$$

$$X_{id}(t+1) < X^{min}$$
$$\Rightarrow x_{id}(t+1) = X^{\min}, v_{id}(t+1) = 0 \qquad (1)$$

7. If the stopping condition is met, go to step 8. Otherwise, $t = t + 1$ and return to step 2.
8. Decode P_g as the best set of patient and compute the fitness.

This framework is starting with I particles, which corresponds with I different set of ambulances and hospitals that are allocated to the injured. Then the particles are moved in the search space and the fitness of each particle is evaluated. The fitness of each particle is calculated by Dijkstra algorithm. Whenever a better allocation of ambulances and hospitals to the injured is found, its corresponding pbest information is updated. This movement process is iterated with an expectation to find better allocations. Finally the particle with best fitness (gbest) decodes.

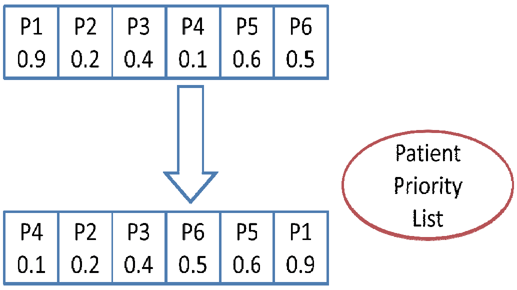
3. SOLUTION REPRESENTATION AND THE DECODING METHOD

At first, the program crates Table 1 to assigns specified hospitals to each injured according to the distance between each injured to each hospital. For example, the nearest hospital to P_1 is H_1, the next nearest hospital is H_3 and the utmost hospital from the first injured is H_2. For example, Table 1 represents the allocated hospitals to each injured corresponding to distance on the network. Then decoding of each particle begins. The dimension of each particle in this problem with P injured is equal to P. Each particle dimension is encoded as a float number. The decoding method for this representation begins with extracting the values of each dimension and after sorting the numbers in ascending order, make a priority list of injured. Schematic example of the whole decoding procedure for the problem is shown in Figure 1.

Table 1. The allocated hospitals to each injured that is calculated by Dijkstra algorithm

Injured ID	Hospitals' ID

P_1	H_1	H_3	H_2
P_2	H_1	H_2	H_3
P_3	H_2	H_1	H_3
P_4	H_3	H_1	H_2
P_5	H_1	H_2	H_3
P_6	H_2	H_3	H_1



P1	P2	P3	P4	P5	P6
0.9	0.2	0.4	0.1	0.6	0.5

P4	P2	P3	P6	P5	P1
0.1	0.2	0.4	0.5	0.6	0.9

Figure 1. Solution representation and decoding steps

Finally, the patient priority list is decoded according to Table 2.

Table 2. Decoding of a particle

Patients	Hospital	Ambulance
P4	H3	A1
P2	H1	A2
P3	H2	A3
P6	H2	A3
P5	H1	A2
P1	H3	A1

In decoding the particles, the capacity of each hospital as a constraint is considered. Also, in assigning each ambulance to each injured, time is considered as a constraint. For example, if we have n ambulances, after serving n injured, $n+1^{th}$injured is served by the ambulance which arrives to the location sooner than the others. In this small instance, for clarifying the solution, the capacity of each hospital is assumed equal to 2 and n is 3. According to the explanations, P_1 should be carried to H_3, because the capacity of H_1 is full. Also, P_4, P_2 *and* P_3 are carried to specified hospitals with ambulances A_1 to A_3. But the next injured,P_6, is carried with the ambulance that arrives to the location sooner than the others.

At the end, the fitness or cost of each particle is calculated by Dijkstra algorithm according to Equation 2 and the result is showed in Table 3.

$$fitness = distance(ambulance - injured) + distance(injured - hospital) \quad (2)$$

Table 3. Final decoded particle and its fitness

Patients	Hospital	Ambulance	Fitness
P4	H3	A1	f1
P2	H1	A2	f2
P3	H2	A3	f3
P6	H2	A3	f4
P5	H1	A2	f5
P1	H3	A1	f6
			∑fi

All of the distances are calculated with Dijkstra algorithm. Then values of pbest, gbest, X_{id}, V_{id} update and the process iterates.

4. COMPUTATIONAL RESULT

A set of computational result is conducted to test the performance of the PSO with the solution representation for solving the emergency services. The data set is in a small district in Tehran shown in Figure 2. The Projected Coordinate System is WGS_1984_UTM_Zone_39N and the Projection is Transverse_Mercator. Hospitals are marked by blue squares and the injured are marked by green squares. Hospitals and injured people are distributed randomly in the whole area. The circle in Figure 2 shows the emergency center where ambulances are originally there.

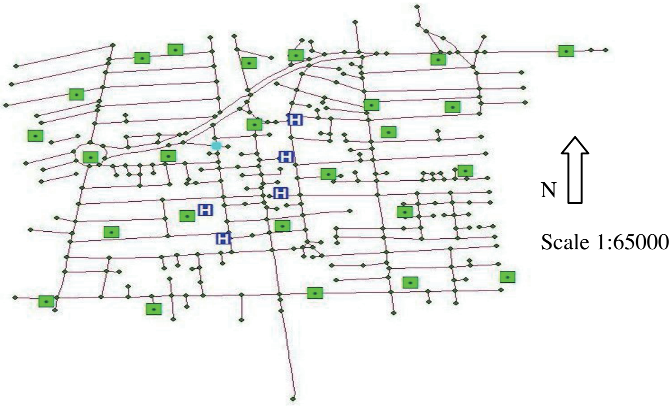


Figure 2. District 6 for implementing the solution representation

The algorithm is implemented on a PC with Intel core 2 Duo 2.5 GHz - 4 GB RAM. The PSO parameters are: Number of Particle, I=100; Number of Iteration, T=500; Number of ambulances, n=13; Number of injured $m = 25$; Number of hospitals is five; the capacity of each hospital is two; the capacity of each ambulance is one; Inertia weight W=4; personal best position acceleration constant, $c_p = 2$; global best position acceleration constant, $c_g = 2$;

The computational results of the solution representation are presented in Table 3.

Table 3. Computational Result

INJURED ID	HOSPITAL ID	AMBULANCE ID
14	90	1
293	251	2
115	90	3
28	90	4
143	215	5
227	251	6
32	90	7
158	201	8
150	215	9
94	90	10
19	90	11
298	251	12
66	215	13
96	134	4
81	134	3
272	251	5
310	215	6
241	215	9
184	201	11
13	134	10
225	201	8
296	215	13
73	134	7
22	134	1
317	215	2

Total Fitness = 28712.2639201484(m)

Table 3 shows that the injured with ID=14 should be carried to hospital with ID=90 by ambulance with ID=1. Figure 3, shows that the more the algorithm iterates, the lower the cost becomes.

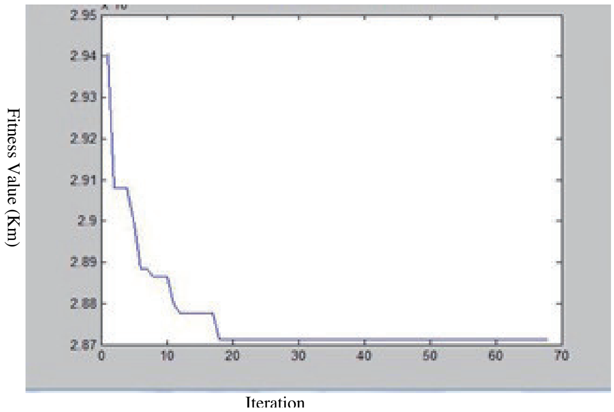


Figure 3. The fitness values across iteration

5. CONCLUSION

This paper presents a solution representation and the corresponding decoding method for solving the emergency services using particle swarm optimization (PSO). The representation is a p dimensional particle for the problem with n ambulances and m injured. The computational result shows that proposed PSO framework with the solution representation is effective for solving the emergency services.

Some further research for applying the proposed method is to use PSO algorithm with Ring topology and compare the results with the proposed algorithm. Also the emergency services can be solved with other evolutionary computing methods like Bee colony.

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