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Parameters Analysis of Pso Algorithm in Intelligent System Optimization

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Abstract: With the rapid development of intelligent system, real time optimization become more and more urgent. Particle Swarm Optimization (PSO) is one of the most effective algorithms in solving such problems. Considered the complexity of intelligent system optimization, speed-up technique is needed. As many optimization problems can be converted to travelling salesman problem, the standard benchmark problem of TSP with 31 cities is employed to analyze the relationship between optimal solution and different parameters. The effect on average of the optimal solution, optimal solution, convergence speed and stability of the optimal solution of different parameters are analyzed. Finally, a comparation with ant colony algorithm is conducted and suitable values of parameters are proposed.

Key words: PSO, TSP, acceleration constants, inertia weight, parameter analysis, intelligent system optimization

INTRODUCTION

With the rapid development of information technology, intelligent system has been widely used in various fields, such as transportation, logistics, etc. However, as the intelligent system is usually complex, the speed-up technique is needed to provide optimization decision support.

Considered the complexity of solving intelligent system optimization, much work has been carried out. Eberhart and Kennedy (1995) introduced particle swarm theory and proposed the PSO algorithm which is simple in concept, few in parameters and easy in implementation. Then, Kennedy and Eberhart (1997) extends the PSO algorithm to a discrete binary version in order to solve discrete problem. Lu *et al*. (2010) presented a new hybrid PSO with mutation for economic dispatch with non-smooth cost function. Menhas *et al*. (2012) analyze various binary coded PSO algorithms in multivariable PID controller design. Considered the complexity of intelligent system optimization, speed-up technique is needed. Engebretsena and Karpinski (2006) studied TSP with bounded metrics. Baltz and Srivastav (2005) proposed an approximation algorithm for the Euclidean bipartite TSP. Benvenutia and Punnen (2012) discussed three value TSP and linkages with the three value linear spanning 2-forests. De Berga *et al*. (2005) gave TSP with neighborhoods of varying size and seek the shortest tour that visits all neighborhoods. Martin *et al*. (1992) considered a new class of optimization heuristics which combine local searches with stochastic sampling methods, allowing one to iterate local optimization heuristics. Lusta and Jaszkiewicz (2010) proposed speed-up techniques for solving large-scale projective TSP.

In this study, we focused on the analyses of influence of PSO algorithm with different parameters. Section 1 introduces the PSO algorithm and benchmark problem. Parameter analysis of the PSO algorithm is studied in section 1 and a comparation with ant colony algorithm is conducted in section 4.

PSO ALGORITHM AND BENCHMARK PROBLEM

PSO algorithm: For the optimization of intelligent system is a combinatorial optimization problem, we should employ the discrete version of PSO. The algorithm of discrete PSO is summarized as follows:

- Initialize an array of particles with random positions and velocities
- Evaluate the desired minimization function
- Compare evaluation with particle's previous best value
- Compare evaluation with group's previous best
- Change velocity
- Move to present position: Loop to step 2 and repeat until a criterion is met

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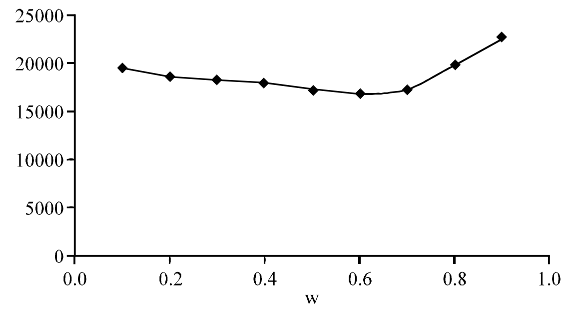


Fig. 1: Average of optimal solution with different w

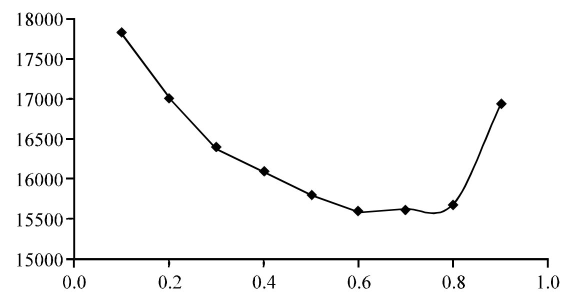


Fig. 2: Optimal solution with different w

Table 1: Coordinates of 31 cities

City No.	x	y	City No.	x	y
1	1304	2312	17	3918	2179
2	3639	1315	18	4061	2370
3	4177	2244	19	3780	2212
4	3712	1399	20	3676	2578
5	3488	1535	21	4029	2838
6	3326	1556	22	4263	2931
7	3238	1229	23	3429	1908
8	4196	1004	24	3507	2367
9	4312	790	25	3394	2643
10	4386	570	26	3439	3201
11	3007	1970	27	2935	3240
12	2562	1756	28	3140	3550
13	2788	1491	29	2545	2357
14	2381	1676	30	2778	2826
15	1332	695	31	2370	2975
16	3715		1678		

Benchmark problem: TSP is one of the classic combinatorial optimization problems in graphic theory and many practical problems can be transformed into TSP, especially the routing problem in intelligent systems optimization. We employed the standard TSP benchmark problem to analyze the influences of different parameter on the result. There are 31 cities and the coordinates of each city is listed in Table 1.

Parameter analysis: In this section we discussed the influence of different parameters.

Inertia weight w: In PSO algorithm, inertia weight is one of the most important adjustable parameters, it is used to control the algorithm's exploitation ability and exploration ability. Larger inertia weight facilitates local search while smaller inertia weight facilitates local search. In order to find a suitable inertia weight to provide a balance between global and local explorations, experiments were conducted.

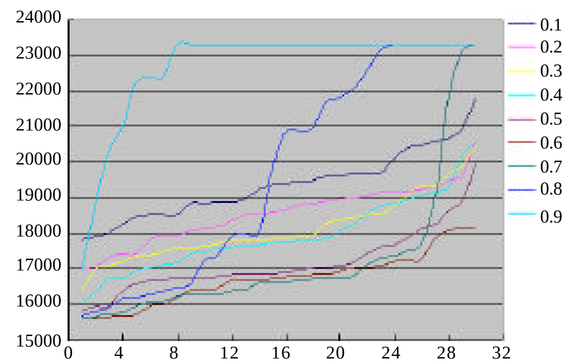


Fig. 3: Stability of optimal solution with different w

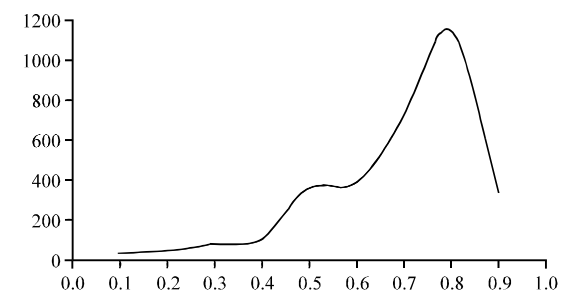


Fig. 4: Convergence speed of optimal solution with different w

Average of the optimal solutions indicates overall optimal value of PSO algorithm. As shown in Fig. 1, the average of the optimal value get best around 0.6 and less than 0.6, change slower, more than 0.6, change faster. Fig. 2 shows the relation between w and optimal solution. It can be seen from Fig. 2 that we can find the optimal solution with w at 0.6-0.8 range. When w is greater than 0.8 or less than 0.6, the solution is getting worse.

From Fig. 3, we can see that the stability decreases with w increase and deteriorate quickly when w is greater than 0.6. Fig. 4 shows the convergence speed of optimal solution with different w. When w is greater than 0.5, the convergence speed of optimal solution increases with w increase until w is greater than 0.8.

Acceleration constant c_1: Acceleration constant c_1 is the acceleration constant used to pull each particle towards pbest, where pbest is the best position associated with the best fitness value of particle obtained so far.

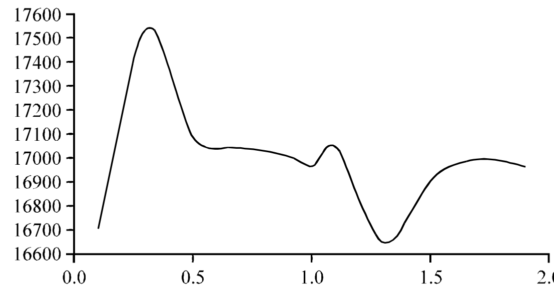


Fig. 5: Average of optimal solution with different c_1

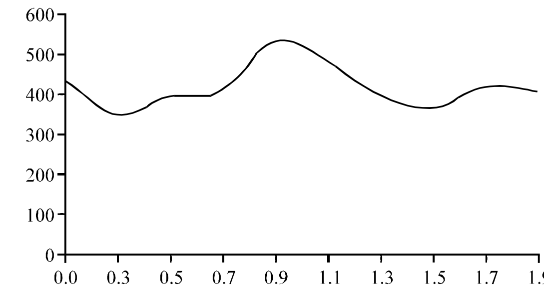


Fig. 8: Convergence speed of optimal solution with different c_1

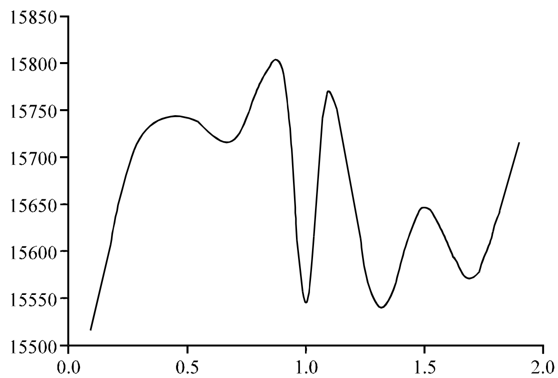


Fig. 6: Optimal solution with different c_1

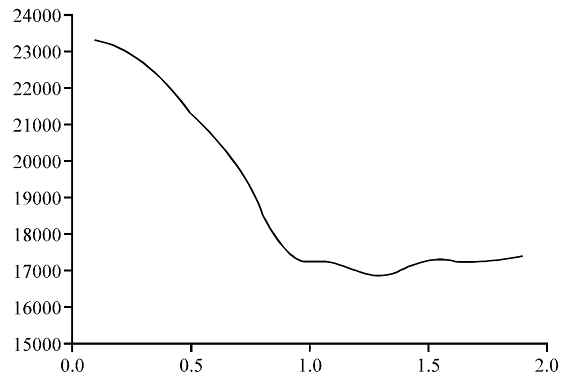


Fig. 9: Average of optimal solution with different c_2

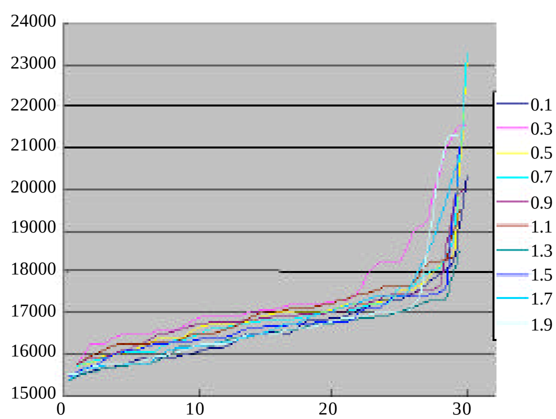


Fig. 7: Stability of optimal solution with different c_1

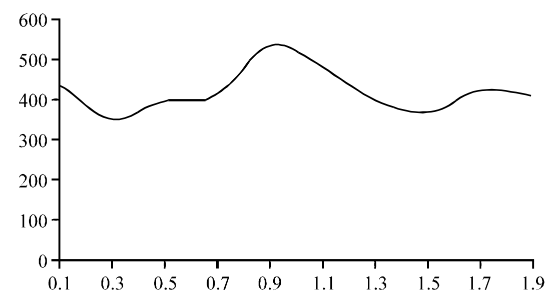


Fig. 10: Optimal solution with different c_2

Figure 5 shows that average of the optimal value get best when c_1 is between 1.0 and 1.5 and get worst when c_1 is less than 0.5. As shown in Fig. 6, the optimal value gets best when the value of c_1 around 1 or 1.3. Figure 7 and 8 show the stability and convergence speed with different c_1 separately. According to Fig. 5-8, set the value of c_1 = 1.3 is suitable.

Acceleration constant c_2: Acceleration constant c_2 is the acceleration constant used to pull each particle towards gbest, where gbest is the best position among all the particles in the swarm.

According to Fig. 9-10, we can see that the average of optimal solution and optimal solution decrease with c_2 increases and become stable after 1.0. Figure 10 and 11 describe the stability and convergence speed of optimal solution with different c_2 respectively. As the curves show, the stability get best around 1.3 and convergence speed get best round 1.4.

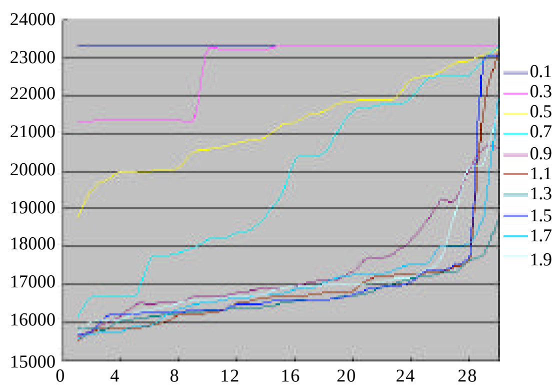


Fig. 11: Stability of optimal solution with different c_2

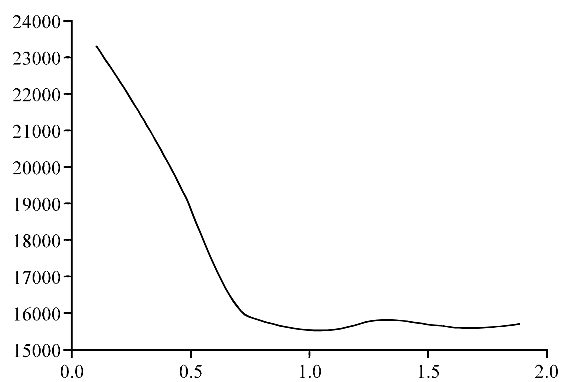
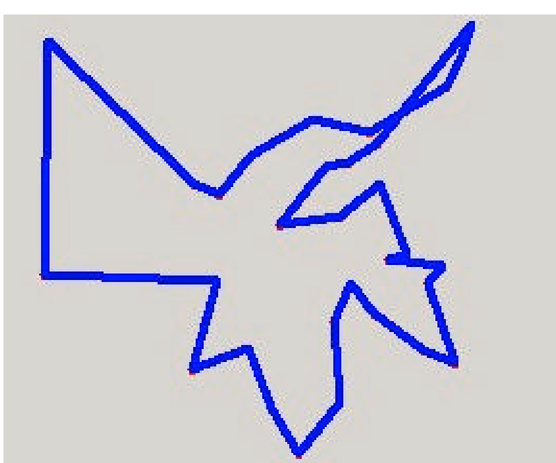
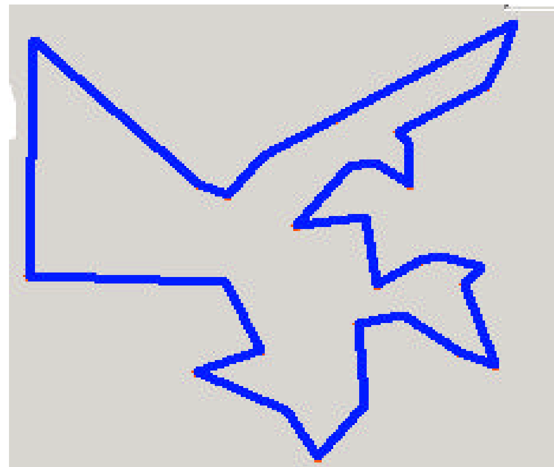


Fig. 12: Convergence speed of optimal solution with different c_2

COMPARATION





CONCLUSIONS

In this study, the relationships between optimal solution and PSO parameters are discussed. The benchmark problem of TSP with 31 cities is employed to analyze the relationship between optimal solution and different parameters. Experiments were conducted to analyze the effects of acceleration constants and inertia weight on optimal solution. According to the result of experiments, $w\in[0.6, 0.8]$, $c_1 = 1.3$, c_2, $\in[1, 1.5]$, is suitable in most of the cases.

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