Comparison of Nature-Inspired and Graph Algorithms Solving Travelling Salesman Problems

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***Abstract*—In this paper we conduct an analysis with the goal of comparing two nature-inspired algorithms and five traditional algorithms from graph theory and integer linear programming based on defined key metrics. We focus first on describing the experiment setup, the input models and the outline of the metrics applied in the analysis part. Aim of the analysis is to compare the performance of nature-based algorithms with more conventional algorithms used in the solving of travelling salesman problems (TSP).**

***Index Terms*—travelling salesman problem, nature-inspired algorithms, combinatorial optimization**

I. Introduction

According to [1]–[3] a Combinatorial Optimization (CO) problem consists of a limited set of problems with unique components. The goal is to find the optimal combination of each component. The CO problem as by [4] can be defined with:
- a set of variables $X = \{x_1, ..., x_n\}$
- variable domains $D_1, ..., D_n$
- constraints among variables
- an $objective function$ f to be minimized, where $f : D_1 x ... x D_n \rightarrow IR^+$

Resulting from this is the set of all possible realizable associations: $S = \{s = \{(x_1, v_1), ..., (x_n, v_n)\} | v_i \in D_i, s$ satisfies all the constraints$\}$. According to Blum and Roli [4] S is denoted as a $search\ space$ and all elements of the set can be considered as candidate solutions. For solving a CO problem, it is necessary to find a solution $s^* \in S$ with minimum objective function value, i.e. $f(s^*) \leq f(s) \forall s \in S$. s^* defines the globally optimal solution of (S, f) and $S^* \subseteq S$ the set of globally optimal solutions. Travelling Salesman Problem (TSP) is one the prominent example for CO problems. We used twenty-two different TSP problems provided by the University of Heidelberg [5] and TSP algorithm suit (AS) provided by University of Oxford [6].

II. Methodology

A MATLAB® based TSP algorithm suite developed by the University of Oxford [6] served as basis for the experiment setup. The AS was extended by implementing an import functionality allowing the solving of a set of TSP instances published by [7] and described in paragraph II-B. In a second step, a two nature-inspired algorithms are implemented along the already available algorithms in [6]. A list of implemented algorithms is described in the paragraph II-A.

A. Optimization Algorithm Selection

Several nature-inspired algorithms can be applied to TSP models. According to Abraham et. al [8] Ant-Colony Optimization (ACO) and Particle Swarm Optimization (PSO) are two most popular algorithm in the field of swarm intelligence. On that account, we choose this two algorithm.

B. Problem Set

The set of TSP instances used in the experiment consists of twenty-two problems varying in size and complexity. The problems were published by [7] and are considered as standard in this field of research. The TSP problem instances vary from a size between 14 and 2392 nodes. In addition, an optimal solution exists for each instance. It is therefore possible to calculate the overall accuracy of an algorithm and compare it to others. We focused on 22 problem instances. All of them are synchronous graphs, meaning the graphs do not contain cycles.

C. Metric Definition

In order to be able to compare the performance of different algorithms, meaningful metrics have been defined. In the implemented solution, successfully solving a TSP instance yields two values:

- Execution time
- Edge distance of the solution

The execution time is a non-deterministic metric due to its platform dependency and various potential side effects during the execution (other running processes on the platform), whereas the edge distance of different algorithms or executions can be directly compared to each other.

III. Optimization Problem

A. Traveling Salesman Problem

The TSP investigates the question, which route the salesman should take in order to travel from one city to the next with minimum distance cost and without visiting a city more than once [1], [6], [9]. The TSP can be modelled as undirected graph[1] or as a complete graph[2] [3]. Traditionally, TSP can be defined as an integer linear programming (ILP) model. Three of the most common formulations of TSP are Dantzig-Fulkerson-Johnson (DFJ), Miller-Tucker-Zemlin (MTZ) and SarinSheraliBhootra (SSB) [3], [9]. In order to calculate the optimal route, e.g. brute force searching method can be used. Hereby, all possible permutations will be formed to find the most favorable one route. Likewise, heuristic methods can be used to find the optimal route, such as nearest neighbours [2].

IV. Optimization Algorithm

Table I show used algorithm, there shortcuts and the naming used in the analysis:

Shortcut	Algorithm	Name in the Analysis
ACO	Ant-Colony Optimization	aco-50 aco-100
SPSO	Standard Particle Swarm Optimization	pso-qpso-50 pso-spso-100 pso-spso-150 pso-spso-200
APSO	Adaptive Particle Swarm Optimization	pso-apso-50 pso-apso-100 pso-apso-150 pso-apso-200
QPSO	Quantum-behaved Particle Swarm Optimization	pso-qpso-50 pso-qpso-100 pso-qpso-150 pso-qpso-200
	Increasing loop algorithm	inc_loop
	Forcefully increasing loop algorithm	f_inc_loop
	Optimal greedy algorithm	opt_greedy
	2-opt algorithm	two_opt

TABLE I
List of used Algorithms and there shorts cuts

A. Ant Colony Optimization

In his Ph.D Thesis, Marco Dorigo introduced in 1992 the Ant Colony Optimization (ACO) algorithm [2], [8]. ACO is a probabilistic approach to solve computational problems which can be reduced to finding good paths through graphs [8].

According to Halimi et al. [2] inspiration for this algorithm comes from the observation of ants colony searching for food. Ants foraging for food are distributed in different directions [10]. Adapted to the TSP, the artificial ant is an agent that moves from one city to the next [2]. In the search for food, ants leave a substance called pheromone along the path, which in turn helps to identify the route later again. The choice of the city to travel is based on the probabilistic function and within this probability the artificial ant selects the new cities by edges, accumulation of pheromone traces and proximity to the ant. On the ACO algorithm, three ideas of ant behavior are transferred: (1) choice of path is based on a high pheromone value, (2) a higher pheromone concentration along shorter paths, and (3) use of the path for communication purposes between the ants [2].

[1]formed through symmetric TSP, where the distance between two cities is the same in any opposite direction

[2]formed through asymmetric TSP, where the path may not exist or the distance in both direction can be different

B. Particle Swarm Optimization

The Particle Swarm Optimization (PSO) was inspired by birds seeking for food and imitates their swarm behavior [8], [10]. PSO search algorithm is initiated with a set of random solutions called particles. Inspired by the behavior of a swarm of birds - synchronized movements, they move without collision and they maintain distance between them-, the population seeks the global optimum. The motion of each particle is governed by a velocity update equation. This strategy involves each individual remembering or recording the places of the best fitness. An individual's best solution or success is called the best particle, and this information is then shared with neighbors. Usually, a swarm is designed by particles in a multidimensional space, and each particle in each iteration has a position and velocity [8], [10]. Besides the standard implementation for the PSO algorithm, we consider two extended version of the algorithm in our analysis. In the following chapters, both of them will be introduced.

1) Adaptive Particle Swarm Optimization: The Adaptive Particle Swarm Optimization algorithm (APSO) is based on the original PSO algorithm. According to [11], it distinguishes itself through three modifications:

1) The search space is divided into multiple segments, like a spider net. Each segment is populated individually, therefore highly increasing the search accuracy of the algorithm.
2) Each sub-swarm shares information with its neighbours. Swarms with higher fitness values will therefore guide their colleges, hence improving their fitness as well. This idea is taken from the flocking behaviour of spiders.
3) APSO uses the fitness value to adjust the learning factors ($c1, c2$). In the standard PSO, the fitness is not taken in consideration.

2) Quantum-behaved Particle Swarm Optimization: The Quantum-behaved Particle Swarm Optimization algorithm (QPSO) is based on the principles of quantum mechanics [12] and was first introduced by [13]. It outperforms the standard implementation of the PSO algorithm, but has less customizable parameters. The computation of the algorithm can be depicted in the flowchart in Figure 1.

1) First the parameters will be initialized
2) Then, the individual fitness values are computed
3) The optimal population history is updated. If a particle has a better fitness than the population's optimum, the optimum is updated.
4) The overall optimum of particles is updated. If the fitness of a particle is lower than the global optimum, it will be replaced by it.
5) Updates all particles by using the quantum-behaved algorithm formula.
6) The algorithm repeats steps two to five until it reaches the maximum number of iterations and terminates.

C. Increasing loop algorithm

Increasing loop is a stochastic algorithm producing a possible solution, which has a high possibility to be optimal. At

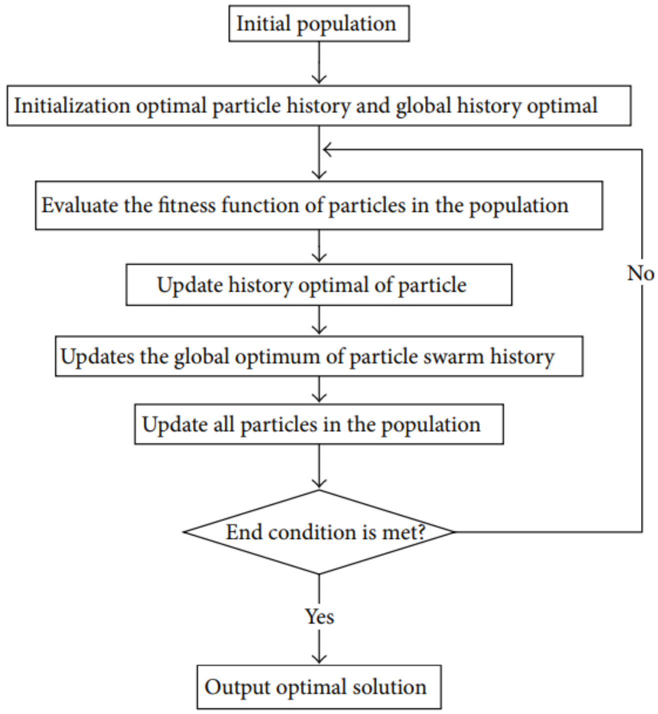


Fig. 1. QPSO algorithm flowchart [12]

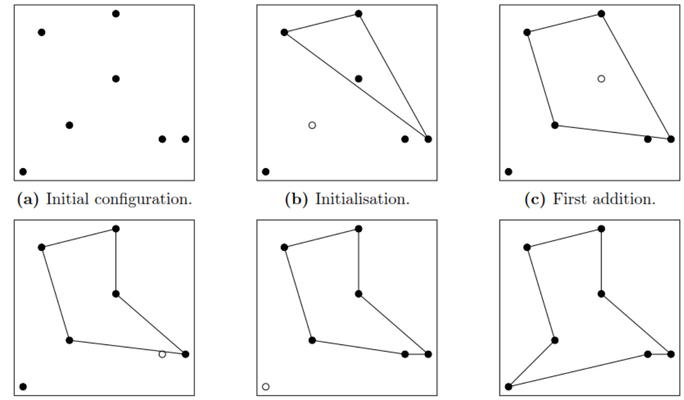
the beginning, the algorithm randomly selects three vertices and forms a loop with them. It then randomly adds another adjusted vertex to the sub-loop and calculate the new distance. The algorithm then calculates if there could be built a shorter loop. It evaluates the added distance from replacing each existing connection. It remembers the increased distance and repeats this for all nodes not in the sub-loop, therefore finding what the global minimal deformation for the sub-loop would be if it included one of the unconnected nodes. The algorithm then forms this new minimal connection, and then recomputes the minimal global deformation. This process will be executed iteratively until it runs out of unconnected vertices. This procedure is visualized in Figure 2.

D. Forcefully increasing loop algorithm

The forcefully increasing loop algorithm is a faster implementation of the increasing loop algorithm IV-C. At the beginning, it randomly selects three vertices and forms a loop with them. It then randomly adds another adjusted vertex to the sub-loop and calculate the new distance. The algorithm then calculates if there could be built a shorter loop.

E. Optimal greedy algorithm

The Optimal greedy algorithm is a subset of the greedy algorithm which follows the heuristic of choosing a locally optimal solution at each step in order to find the global optimum [15]. It does usually not produce an optimal solution, but it is a reasonable trade-off between computation time and optimality. The Optimal greedy algorithm differs from this by using specific starting nodes. It compares the edge cost of all computed routes and chooses the path with the minimal distance.



(a) Initial configuration. **(b)** Initialisation. **(c)** First addition. **(d)** Intermediate addition. **(e)** Final addition. **(f)** Final route.

Fig. 2. Increasing loop algorithm [14]

F. 2-opt algorithm

2-opt is an iterative algorithm [16] optimizing Hamiltonian cycles by randomly removing two edges and then altering the cycle by cross-linking the four nodes with one another as depicted in Figure 3. Afterwards, the distance of the cycle is calculated and compared to the previously best distance and takes whichever is lower. For this analysis, the algorithm terminates if it does not improve its best solution over 1000 consecutive iterations.

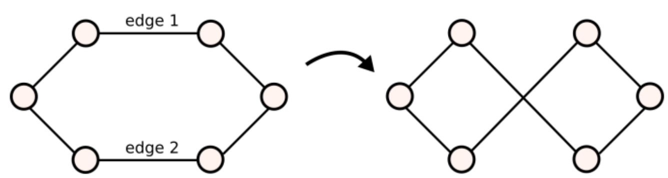


Fig. 3. Hamiltonian cycle optimization [14]

V. Performance Comparison of selected Optimization Algorithm

This chapter discuss the output of the simulations using MATLAB® [3]. The output was analyzed according to the execution time and the distance compared to optimal distance. The execution time is the duration in seconds used to solve a specific TSP problem. For the nature-inspired algorithms ACO and PSO, different population sizes (50, 100, 150 and 200) were defined. Because of time related reasons the ACO algorithm was running only with a population of 50 and 100 ants. Population sizes of 150 and 200 ants would have resulted in computation times of several days. Table II provides information about the specified parameters sets used in the algorithms.

[3] The analysis was conducted on desktop computer with a Ryzen 7 1700 3.7 GHz CPU and 16GB Dual Channel DDR4 RAM @2400 MHz

Algo.	Parameters
ACO	Iteration = 200 Num of Ants = 50, 100 α (pheromone exponent) = 1 β (desirability exponent) = 1 ρ (evaporation rate) = 0.5
APSO	Iteration = 400 Population Size = 50, 100, 150, 200 α = 0.8 β = 0.9 γ = 0.99
QPSO	Iteration = 400 Population Size = 50, 100, 150, 200 α min. = 0.08 α max. = 0.9
SPSO	Iteration = 400 Population Size = 50, 100, 150, 200 c1,c2 (learning factors) = 1.0 w (momentum of inertia) = 0.9

TABLE II
PARAMETER SETTINGS FOR NATURE ALGORITHMS

In the analysis, each algorithm was executed 100 times with twenty-two benchmark problems from TSPlib [7]. Table III shows the selected TSP problems with the optimal distance. The TSP problems were grouped according to their node size: ”Small” $(n < 100)$, ”Medium” $(99 < n < 200)$ and ”Big” $(n > 199)$. The partitioning was made by taking into account the number of nodes and the time needed to solve the TSP problems.

TSP	Optimal Distance	Nodes	Classification
berlin52	7542	52	Small
burma14	3323	14	Small
eil51	426	51	Small
eil76	538	76	Small
gr96	55209	96	Small
pr76	108159	76	Small
st70	675	70	Small
ulysses16	6859	16	Small
ulysses22	7013	22	Small
ch130	6110	130	Medium
ch150	6528	150	Medium
eil101	629	101	Medium
kroA100	21282	100	Medium
kroC100	20749	100	Medium
kroD100	21294	100	Medium
lin105	14379	105	Medium
rd100	7910	100	Medium
gr202	40160	202	Big
gr666	294358	666	Big
pr1002	259045	1002	Big
pr2392	378032	2392	Big
tsp225	3916	225	Big

TABLE III
CLASSIFICATION OF TSP BASED ON NODE SIZE

A. Execution Time

Execution time was compared with the number of nodes and it was also examined whether the population size had an influence on it. Furthermore, the algorithms and TSP instances were considered. The Table VI shows an overview of the execution time (Time (s)), mean distance (Avg. Dist.), optimal distance (Opt.Dist), percentage deviation from the optimal distance (%), minimum and maximum distance (MIN/MAX) and the standard deviation (σ) split by TSP and algorithm. Figures 4, 5 and 6 show the execution time range for different algorithms grouped by TSP classification. Figure 8 shows an overall range of execution time grouped by TSP classification.

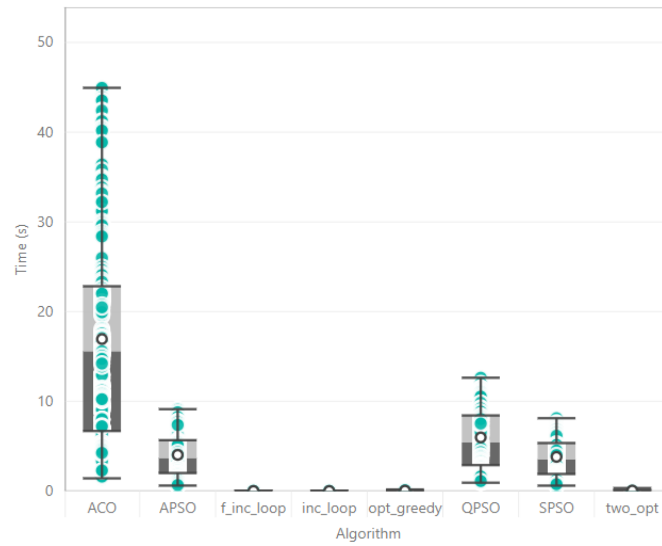


Fig. 4. Overall execution time for TSP-Small

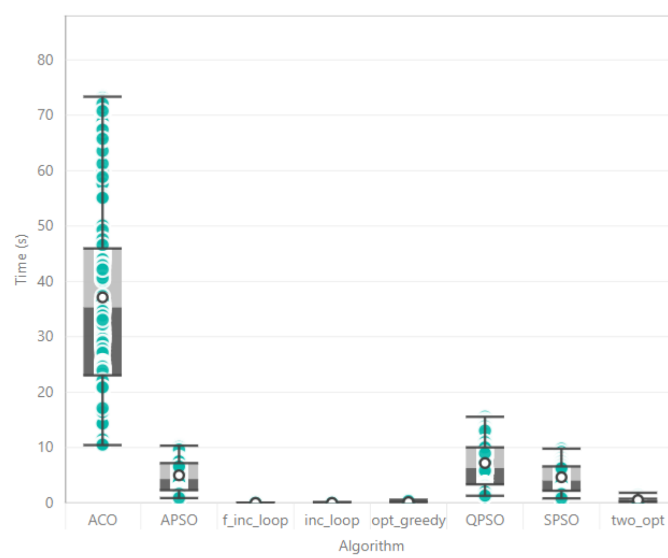


Fig. 5. Overall execution time for TSP-Medium

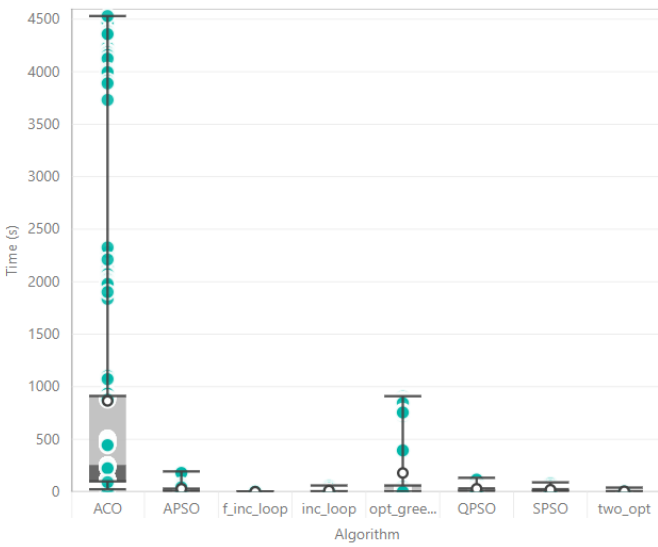


Fig. 6. Overall execution time for TSP-Medium

The execution time depends strongly on the amount of nodes. Figure 7 depicts the influence of the node size on the execution time. As the number of nodes increased, the two nature-inspired algorithms required more time to execute, especially the ACO algorithm scales bad with the number of nodes. The number of the population with ACO algorithm had a influence on the execution time. Compared to the result with population 50, the ACO with population 100 had almost twice as long. Opt_greedy algorithm came right after the ACO.

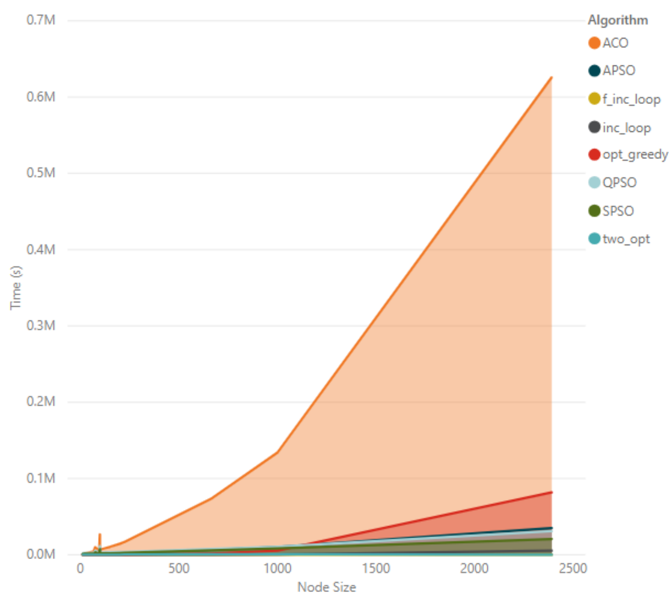


Fig. 7. Comparison time to node size

B. Edge Distance of the Solution

Table IV and V shows the average distance of each algorithm based on the TSP problem. The percentage deviation of the individual algorithms from the optimal distance was also taken into account. Especially PSO appears to be very unfavorable when the number of nodes increases. The higher the number of nodes, the greater the percentage deviation from the optimal distance. For TSP problems with a very low number of nodes, such as Burma with 14 or Ulysses with 16, the PSO algorithm (APSO and QPSO) could show very good results with a population of 150. The ACO followed the PSO with significantly better results. The two nature-inspired algorithms show a significantly lower result here as well.

TSP	aco-100	aco-50	f_inc_loop	inc_loop	opt_greedy	pso-apso-100	pso-apso-150	pso-apso-200	pso-apso-50
berlin52	9.21 %	10.58 %	11.71 %	16.91 %	8.49 %	155.87 %	135.43 %	139.96 %	139.4 %
burma14	0.05 %	0.19 %	3.13 %	3.43 %	15.59 %	9.75 %	13.63 %	15.53 %	7.88 %
ch130	25.97 %	28.87 %	9.17 %	15.49 %	17.82 %	534.96 %	539.04 %	546.56 %	537.62 %
ch150	26.77 %	29.17 %	11.28 %	18.99 %	8.43 %	599.05 %	592.51 %	604.11 %	588.65 %
eil101	27.62 %	29.37 %	11.08 %	14.18 %	17.07 %	287.75 %	298.16 %	307.47 %	303.69 %
eil51	13.6 %	15.73 %	8.15 %	13.21 %	18.73 %	128.5 %	125.31 %	121.95 %	165.03 %
eil76	18.6 %	20.4 %	10.07 %	12.47 %	13.88 %	235.87 %	212 %	218.85 %	246.27 %
gr202	31.49 %	34.46 %	9.36 %	15.97 %	17.18 %	425.93 %	392.54 %	427.59 %	415.26 %
gr666	55.83 %	63.66 %	13.67 %	17.91 %	18.99 %	1378.37 %	1396.86 %	1302.61 %	1425.98 %
gr96	18.22 %	19.55 %	8.56 %	17.29 %	15.82 %	278.72 %	310.73 %	230.43 %	329.35 %
kroA100	22.64 %	24.88 %	8.5 %	15.07 %	16.05 %	539.49 %	540.91 %	509.1 %	544.63 %
kroC100	20.41 %	22.43 %	8.97 %	17.71 %	13.58 %	541 %	534.47 %	543.35 %	558.78 %
kroD100	20.41 %	22.2 %	8.83 %	16.04 %	16.73 %	498.77 %	490.18 %	511.62 %	528.97 %
lin105	16.49 %	18.65 %	10.3 %	18.39 %	17.81 %	457.53 %	399.37 %	377.33 %	415.26 %
pr1002	75.19 %	86.16 %	12.77 %	16.28 %	20.53 %	2056.53 %	2118.24 %	2019.16 %	2100.62 %
pr2392	100.72 %	119.04 %	15.76 %	20.62 %	21.36 %	3573.67 %	3478.95 %	3503.32 %	3512.35 %
pr76	13.46 %	14.79 %	7.27 %	13.2 %	21.04 %	190.59 %	231.95 %	202.72 %	220.18 %
rd100	25.05 %	27.15 %	9.71 %	14.88 %	19.18 %	459.74 %	466.3 %	458.18 %	428.55 %
st70	18.09 %	19.83 %	7.34 %	11.88 %	12.84 %	267.49 %	292.4 %	267.04 %	311.54 %
tsp225	40.86 %	45.71 %	10.29 %	14.02 %	18.31 %	725.32 %	729.33 %	732.37 %	749.43 %
ulysses16	0.02 %	0.17 %	3.25 %	6.73 %	15.8 %	7.28 %	1.36 %	8.3 %	7.61 %
ulysses22	0.76 %	1.08 %	4.27 %	8.56 %	16.64 %	36.87 %	29.39 %	36.96 %	36.6 %

TABLE IV
DEVIATION OF DISTANCE TO OPTIMAL DISTANCE - PART I

TSP	pso-qpso-100	pso-qpso-150	pso-qpso-200	pso-qpso-50	pso-spso-100	pso-spso-150	pso-spso-200	pso-spso-50	two_opt
berlin52	142.74 %	107.47 %	141.08 %	203.87 %	166.27 %	130.15 %	185.08 %	177.45 %	10.74 %
burma14	11.13 %	2.14 %	1.38 %	3.7 %	2.02 %	5.54 %	15.44 %	17.12 %	2.23 %
ch130	542.74 %	529.64 %	539.24 %	553.38 %	530.77 %	515.55 %	526.72 %	540.34 %	20.92 %
ch150	608.32 %	591.45 %	602.75 %	621.46 %	575.3 %	597.92 %	582.28 %	626.78 %	29.31 %
eil101	351.51 %	341.02 %	318.54 %	324.41 %	328.65 %	329.67 %	321.56 %	333.73 %	17.89 %
eil51	144.51 %	180.54 %	169.21 %	154.39 %	156.37 %	177.71 %	142.68 %	230.62 %	9.07 %
eil76	266.02 %	266.09 %	274.91 %	269.84 %	270.91 %	238.79 %	262.01 %	274.64 %	14.24 %
gr202	269.39 %	260.22 %	258.15 %	301.92 %	400.36 %	382.3 %	380.11 %	383.67 %	22.09 %
gr666	1058.03 %	1030.08 %	1057.8 %	1114.13 %	1287.76 %	1274.82 %	1225.52 %	1285.74 %	42.42 %
gr96	198.77 %	152.71 %	173.46 %	194.53 %	292.31 %	205.94 %	229.31 %	341.14 %	14.83 %
kroA100	523.55 %	519.44 %	531.37 %	553.89 %	530.88 %	519.21 %	545.19 %	534.85 %	18.41 %
kroC100	529.78 %	550.26 %	532.65 %	551.43 %	526.93 %	521.91 %	502.21 %	545.29 %	19.76 %
kroD100	518 %	505.71 %	508.41 %	529.77 %	487.37 %	493.61 %	506.85 %	470.75 %	17.05 %
lin105	290.5 %	237.59 %	221.36 %	269.62 %	359.49 %	340.52 %	300.7 %	352.87 %	19.9 %
pr1002	1696.65 %	1615.92 %	1591.54 %	1756.37 %	1909.26 %	1818.39 %	1864.57 %	1947.8 %	34.43 %
pr2392	3270.02 %	3229.1 %	3080.47 %	3277.79 %	3392.83 %	3372.39 %	3365.01 %	3499.16 %	0.01 %
pr76	152.07 %	126.97 %	110.76 %	168.91 %	231.57 %	192.43 %	154.7 %	256.06 %	19.71 %
rd100	474.41 %	469.83 %	465.09 %	475.46 %	454.04 %	447.49 %	470.2 %	470.17 %	19.35 %
st70	326.56 %	326.66 %	331.2 %	286.17 %	283.47 %	290.31 %	330.54 %	334.75 %	12.02 %
tsp225	524.38 %	546.69 %	496.81 %	545.5 %	689.85 %	628.21 %	635.15 %	708.9 %	32.41 %
ulysses16	6.21 %	1.33 %	4.07 %	11.78 %	6.27 %	8.89 %	5.79 %	21.11 %	1.52 %
ulysses22	22.09 %	30.29 %	32.88 %	17.8 %	35.18 %	20.45 %	20.55 %	30.12 %	2.33 %

TABLE V
DEVIATION OF DISTANCE TO OPTIMAL DISTANCE - PART II

VI. CONCLUSION

In conclusion, our conducted analysis shows that traditional stochastic and heuristic graph algorithms outperformed both the ACO and the three tested implementations of the PSO algorithm. Especially the ACO algorithm seems to scale rather poorly with node count which concluded in computation times of several hours for bigger ant colony sizes if applied on the largest TSP instances. This is a significant deviation from the other tested algorithms. It was to be expected that the execution time of the optimal greedy algorithm would be inferior compared to the other heuristic and stochastic algorithms due to its linear scaling.

It has to be stated that we only tested one parameter setting configuration per nature-inspired algorithm. Repeating the scenarios with additional parameter settings could improve both accuracy and execution time. In an extension of this paper, it would therefore be interesting to take a look at the possible impact of different parameter settings for both ACO and PSO.

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APPENDIX

TSP	Algorithm	Time (s)	Avg.Dist.	Opt.Dist.	%	σ	MIN	MAX
berlin52	aco-100	2265.04	8236.87	7542	9.21 %	184.53	7700.07	8607.07
	aco-50	1159.05	8339.96	7542	10.58 %	185.09	7738.56	8797.58
	f_inc_loop	0.13	8425.37	7542	11.71 %	282.64	7694.86	9061.57
	inc_loop	0.14	8817.66	7542	16.91 %	194.39	8177.8	9185.67
	opt_greedy	4.27	8182.19	7542	8.49 %	0	8182.19	8182.19
	pso-apso-100	305.17	19298.09	7542	155.87 %	0	19298.09	19298.09
	pso-apso-150	526.19	17755.99	7542	135.43 %	0	17755.99	17755.99
	pso-apso-200	667.88	18097.81	7542	139.96 %	0	18097.81	18097.81
	pso-apso-50	177.5	18055.21	7542	139.4 %	0	18055.21	18055.21
	pso-qpso-100	457.97	18307.2	7542	142.74 %	0	18307.2	18307.2
	pso-qpso-150	744.7	15647.73	7542	107.47 %	0	15647.73	15647.73
	pso-qpso-200	979.59	18182.07	7542	141.08 %	0	18182.07	18182.07
	pso-qpso-50	242.31	22918.04	7542	203.87 %	0	22918.04	22918.04
	pso-spso-100	292.28	20082.45	7542	166.27 %	0	20082.45	20082.45
	pso-spso-150	477.02	17357.86	7542	130.15 %	0	17357.86	17357.86
	pso-spso-200	595.17	21500.51	7542	185.08 %	0	21500.51	21500.51
	pso-spso-50	154.89	20925.59	7542	177.45 %	0	20925.59	20925.59
	two_opt	8.25	8352.34	7542	10.74 %	313.98	7659.25	9281.38
burma14	aco-100	581.63	3324.66	3323	0.05 %	4.6	3323	3346
	aco-50	310.18	3329.23	3323	0.19 %	9.32	3323	3359
	f_inc_loop	0.03	3427.14	3323	3.13 %	90.67	3323	3734
	inc_loop	0.03	3436.91	3323	3.43 %	73.06	3336	3684
	opt_greedy	0.18	3841	3323	15.59 %	0	3841	3841
	pso-apso-100	258.62	3647	3323	9.75 %	0	3647	3647
	pso-apso-150	422.94	3776	3323	13.63 %	0	3776	3776
	pso-apso-200	555.07	3839	3323	15.53 %	0	3839	3839
	pso-apso-50	132.75	3585	3323	7.88 %	0	3585	3585
	pso-qpso-100	396.49	3693	3323	11.13 %	0	3693	3693
	pso-qpso-150	644.15	3394	3323	2.14 %	0	3394	3394
	pso-qpso-200	837.16	3369	3323	1.38 %	0	3369	3369
	pso-qpso-50	205.38	3446	3323	3.7 %	0	3446	3446
	pso-spso-100	255.12	3390	3323	2.02 %	0	3390	3390
	pso-spso-150	415.52	3507	3323	5.54 %	0	3507	3507
	pso-spso-200	519.13	3836	3323	15.44 %	0	3836	3836
	pso-spso-50	131.89	3892	3323	17.12 %	0	3892	3892
	two_opt	0.35	3397.18	3323	2.23 %	72.44	3323	3565
ch130	aco-100	5885.39	7696.77	6110	25.97 %	173.74	7139.54	8024.73
	aco-50	2960.71	7873.82	6110	28.87 %	158.56	7497.14	8269.16
	f_inc_loop	0.24	6670.1	6110	9.17 %	155.72	6362.63	7092.71
	inc_loop	0.97	7056.62	6110	15.49 %	167.98	6640.12	7500.79
	opt_greedy	26.9	7198.74	6110	17.82 %	0	7198.74	7198.74
	pso-apso-100	398.63	38795.89	6110	534.96 %	0	38795.89	38795.89
	pso-apso-150	649.1	39045.1	6110	539.04 %	0	39045.1	39045.1
	pso-apso-200	858.8	39504.72	6110	546.56 %	0	39504.72	39504.72
	pso-apso-50	205.47	38958.32	6110	537.62 %	0	38958.32	38958.32
	pso-qpso-100	591.76	39271.63	6110	542.74 %	0	39271.63	39271.63
	pso-qpso-150	918.76	38471.07	6110	529.64 %	0	38471.07	38471.07
	pso-qpso-200	1283.06	39057.81	6110	539.24 %	0	39057.81	39057.81
	pso-qpso-50	302.79	39921.69	6110	553.38 %	0	39921.69	39921.69
	pso-spso-100	376.75	38539.8	6110	530.77 %	0	38539.8	38539.8

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TABLE VI – continued from previous page

TSP	Algorithm	Time (s)	Avg.Dist.	Opt.Dist.	%	σ	MIN	MAX
	pso-spso-150	595.83	37609.83	6110	515.55 %	0	37609.83	37609.83
	pso-spso-200	787.42	38292.59	6110	526.72 %	0	38292.59	38292.59
	pso-spso-50	194.45	39125.04	6110	540.34 %	0	39125.04	39125.04
	two_opt	89.91	7388.01	6110	20.92 %	349.67	6879.27	8428.68
ch150	aco-100	6841.79	8275.68	6528	26.77 %	175.28	7796.37	8664.78
	aco-50	3436.79	8432.12	6528	29.17 %	211.82	7713.76	8857.32
	f_inc_loop	0.27	7264.3	6528	11.28 %	151.16	6906.88	7579.71
	inc_loop	1.2	7767.65	6528	18.99 %	150.45	7394.53	8160.11
	opt_greedy	25.9	7078.44	6528	8.43 %	0	7078.44	7078.44
	pso-apso-100	421.71	45634.01	6528	599.05 %	0	45634.01	45634.01
	pso-apso-150	678.38	45206.8	6528	592.51 %	0	45206.8	45206.8
	pso-apso-200	885.95	45964.54	6528	604.11 %	0	45964.54	45964.54
	pso-apso-50	217.6	44954.75	6528	588.65 %	0	44954.75	44954.75
	pso-qpso-100	620.34	46238.99	6528	608.32 %	0	46238.99	46238.99
	pso-qpso-150	964.53	45138.02	6528	591.45 %	0	45138.02	45138.02
	pso-qpso-200	1269.07	45875.31	6528	602.75 %	0	45875.31	45875.31
	pso-qpso-50	317.47	47097.2	6528	621.46 %	0	47097.2	47097.2
	pso-spso-100	400.09	44083.85	6528	575.3 %	0	44083.85	44083.85
	pso-spso-150	625.08	45559.98	6528	597.92 %	0	45559.98	45559.98
	pso-spso-200	802.1	44539.31	6528	582.28 %	0	44539.31	44539.31
	pso-spso-50	206.55	47443.96	6528	626.78 %	0	47443.96	47443.96
	two_opt	153.17	8441.34	6528	29.31 %	461.54	7609.29	9903.75
eil101	aco-100	4408.35	802.7	629	27.62 %	12.07	767.9	827.1
	aco-50	2211.07	813.76	629	29.37 %	15.82	761.12	843.16
	f_inc_loop	0.17	698.67	629	11.08 %	10.93	672.02	723.06
	inc_loop	0.47	718.18	629	14.18 %	11.39	690.33	749.92
	opt_greedy	10.34	736.37	629	17.07 %	0	736.37	736.37
	pso-apso-100	367.69	2438.94	629	287.75 %	0	2438.94	2438.94
	pso-apso-150	585.46	2504.42	629	298.16 %	0	2504.42	2504.42
	pso-apso-200	759.41	2563	629	307.47 %	0	2563	2563
	pso-apso-50	188.11	2539.24	629	303.69 %	0	2539.24	2539.24
	pso-qpso-100	541.49	2839.98	629	351.51 %	0	2839.98	2839.98
	pso-qpso-150	845.33	2774.02	629	341.02 %	0	2774.02	2774.02
	pso-qpso-200	1097.26	2632.6	629	318.54 %	0	2632.6	2632.6
	pso-qpso-50	276.47	2669.53	629	324.41 %	0	2669.53	2669.53
	pso-spso-100	347.16	2696.21	629	328.65 %	0	2696.21	2696.21
	pso-spso-150	556.1	2702.61	629	329.67 %	0	2702.61	2702.61
	pso-spso-200	692.92	2651.63	629	321.56 %	0	2651.63	2651.63
	pso-spso-50	180.17	2728.15	629	333.73 %	0	2728.15	2728.15
	two_opt	21.99	741.55	629	17.89 %	20.61	703.57	822.05
eil51	aco-100	2124.31	483.95	426	13.6 %	10.27	456.95	503.17
	aco-50	1056.01	493	426	15.73 %	10.46	460.14	514.75
	f_inc_loop	0.08	460.73	426	8.15 %	10.18	439.41	489.43
	inc_loop	0.13	482.26	426	13.21 %	13.9	446.06	515.02
	opt_greedy	2.42	505.77	426	18.73 %	0	505.77	505.77
	pso-apso-100	308.1	973.39	426	128.5 %	0	973.39	973.39
	pso-apso-150	495.29	959.8	426	125.31 %	0	959.8	959.8
	pso-apso-200	630.19	945.51	426	121.95 %	0	945.51	945.51
	pso-apso-50	155.37	1129.03	426	165.03 %	0	1129.03	1129.03
	pso-qpso-100	461.57	1041.62	426	144.51 %	0	1041.62	1041.62
	pso-qpso-150	736.83	1195.12	426	180.54 %	0	1195.12	1195.12

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TABLE VI – continued from previous page

TSP	Algorithm	Time (s)	Avg.Dist.	Opt.Dist.	%	σ	MIN	MAX
	pso-qpso-200	941.31	1146.84	426	169.21 %	0	1146.84	1146.84
	pso-qpso-50	234.9	1083.72	426	154.39 %	0	1083.72	1083.72
	pso-spso-100	294.32	1092.16	426	156.37 %	0	1092.16	1092.16
	pso-spso-150	465.3	1183.06	426	177.71 %	0	1183.06	1183.06
	pso-spso-200	596.36	1033.83	426	142.68 %	0	1033.83	1033.83
	pso-spso-50	151.1	1408.44	426	230.62 %	0	1408.44	1408.44
	two_opt	3.16	464.66	426	9.07 %	13.13	444.48	502.73
eil76	aco-100	3251.41	638.04	538	18.6 %	13.01	590.11	662.27
	aco-50	1635.36	647.74	538	20.4 %	14.24	612.15	679.72
	f_inc_loop	0.15	592.18	538	10.07 %	10.11	568.63	615.62
	inc_loop	0.26	605.07	538	12.47 %	13.12	575.05	632.54
	opt_greedy	6.64	612.66	538	13.88 %	0	612.66	612.66
	pso-apso-100	334.95	1806.96	538	235.87 %	0	1806.96	1806.96
	pso-apso-150	532	1678.56	538	212 %	0	1678.56	1678.56
	pso-apso-200	694.19	1715.39	538	218.85 %	0	1715.39	1715.39
	pso-apso-50	169.35	1862.94	538	246.27 %	0	1862.94	1862.94
	pso-qpso-100	500.63	1969.19	538	266.02 %	0	1969.19	1969.19
	pso-qpso-150	806.52	1969.55	538	266.09 %	0	1969.55	1969.55
	pso-qpso-200	1017.27	2016.99	538	274.91 %	0	2016.99	2016.99
	pso-qpso-50	251.74	1989.73	538	269.84 %	0	1989.73	1989.73
	pso-spso-100	324.87	1995.52	538	270.91 %	0	1995.52	1995.52
	pso-spso-150	511.66	1822.66	538	238.79 %	0	1822.66	1822.66
	pso-spso-200	653.7	1947.61	538	262.01 %	0	1947.61	1947.61
	pso-spso-50	162.73	2015.59	538	274.64 %	0	2015.59	2015.59
	two_opt	12.41	614.62	538	14.24 %	17.86	574.1	662.89
gr202	aco-100	9641.57	52804.79	40160	31.49 %	715.43	50758	54222
	aco-50	4812.57	53999.84	40160	34.46 %	934.6	50852	55933
	f_inc_loop	0.44	43920.47	40160	9.36 %	777.07	42104	45561
	inc_loop	2.59	46574.78	40160	15.97 %	468.46	44624	47454
	opt_greedy	50.88	47060	40160	17.18 %	0	47060	47060
	pso-apso-100	495.79	211214	40160	425.93 %	0	211214	211214
	pso-apso-150	792.25	197806	40160	392.54 %	0	197806	197806
	pso-apso-200	1030.69	211880	40160	427.59 %	0	211880	211880
	pso-apso-50	255.18	206927	40160	415.26 %	0	206927	206927
	pso-qpso-100	699.9	148348	40160	269.39 %	0	148348	148348
	pso-qpso-150	1090.58	144666	40160	260.22 %	0	144666	144666
	pso-qpso-200	1406.27	143832	40160	258.15 %	0	143832	143832
	pso-qpso-50	357.53	161412	40160	301.92 %	0	161412	161412
	pso-spso-100	459.79	200944	40160	400.36 %	0	200944	200944
	pso-spso-150	717.36	193691	40160	382.3 %	0	193691	193691
	pso-spso-200	914.54	192811	40160	380.11 %	0	192811	192811
	pso-spso-50	237.6	194242	40160	383.67 %	0	194242	194242
	two_opt	77.51	49031.62	40160	22.09 %	1943.55	45719	55583
gr666	aco-100	48927.56	458693.54	294358	55.83 %	7552.12	430686	469732
	aco-50	24647.11	481753.34	294358	63.66 %	8828.58	456603	497367
	f_inc_loop	4.12	334608.28	294358	13.67 %	5031.84	320830	354021
	inc_loop	114.27	347084.87	294358	17.91 %	4158.42	337200	360891
	opt_greedy	1603.41	350243	294358	18.99 %	0	350243	350243
	pso-apso-100	1300.9	4351706	294358	1378.37 %	0	4351706	4351706
	pso-apso-150	2028.77	4406126	294358	1396.86 %	0	4406126	4406126
	pso-apso-200	2738.81	4128698	294358	1302.61 %	0	4128698	4128698

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TABLE VI – continued from previous page

TSP	Algorithm	Time (s)	Avg.Dist.	Opt.Dist.	%	σ	MIN	MAX
	pso-apso-50	636.98	4491834	294358	1425.98 %	0	4491834	4491834
	pso-qpso-100	1509.97	3408750	294358	1058.03 %	0	3408750	3408750
	pso-qpso-150	2280.39	3326477	294358	1030.08 %	0	3326477	3326477
	pso-qpso-200	2952.13	3408083	294358	1057.8 %	0	3408083	3408083
	pso-qpso-50	760.93	3573902	294358	1114.13 %	0	3573902	3573902
	pso-spso-100	1127.73	4084973	294358	1287.76 %	0	4084973	4084973
	pso-spso-150	1743.18	4046883	294358	1274.82 %	0	4046883	4046883
	pso-spso-200	2228.19	3901777	294358	1225.52 %	0	3901777	3901777
	pso-spso-50	582.58	4079040	294358	1285.74 %	0	4079040	4079040
	two_opt	841.23	419215.5	294358	42.42 %	4071.68	406334	423710
gr96	aco-100	4144.42	65268.96	55209	18.22 %	1490.16	60767	67823
	aco-50	2086.73	66004.87	55209	19.55 %	1656.13	61945	69582
	f_inc_loop	0.17	59932.82	55209	8.56 %	1653.61	56070	64670
	inc_loop	0.39	64756.28	55209	17.29 %	2841.87	58147	70243
	opt_greedy	9.07	63945	55209	15.82 %	0	63945	63945
	pso-apso-100	361.38	209085	55209	278.72 %	0	209085	209085
	pso-apso-150	584.86	226759	55209	310.73 %	0	226759	226759
	pso-apso-200	750.74	182426	55209	230.43 %	0	182426	182426
	pso-apso-50	183.05	237038	55209	329.35 %	0	237038	237038
	pso-qpso-100	526.09	164948	55209	198.77 %	0	164948	164948
	pso-qpso-150	836.18	139518	55209	152.71 %	0	139518	139518
	pso-qpso-200	1078.54	150974	55209	173.46 %	0	150974	150974
	pso-qpso-50	273.17	162608	55209	194.53 %	0	162608	162608
	pso-spso-100	342.47	216591	55209	292.31 %	0	216591	216591
	pso-spso-150	550.34	168904	55209	205.94 %	0	168904	168904
	pso-spso-200	686.35	181811	55209	229.31 %	0	181811	181811
	pso-spso-50	182.51	243547	55209	341.14 %	0	243547	243547
	two_opt	5.65	63394.18	55209	14.83 %	2668.02	58766	70052
kroA100	aco-100	4407.2	26100.86	21282	22.64 %	611.85	24418.46	27162.83
	aco-50	2239.46	26577.57	21282	24.88 %	768.01	24613.68	28493.24
	f_inc_loop	0.65	23091.76	21282	8.5 %	720.78	21762.51	25177.63
	inc_loop	2.22	24488.63	21282	15.07 %	680.05	22560.99	26521.42
	opt_greedy	13.78	24698.5	21282	16.05 %	0	24698.5	24698.5
	pso-apso-100	372.94	136097.32	21282	539.49 %	0	136097.32	136097.32
	pso-apso-150	599.36	136398.7	21282	540.91 %	0	136398.7	136398.7
	pso-apso-200	778.13	129627.75	21282	509.1 %	0	129627.75	129627.75
	pso-apso-50	189.29	137190.23	21282	544.63 %	0	137190.23	137190.23
	pso-qpso-100	553.05	132703.14	21282	523.55 %	0	132703.14	132703.14
	pso-qpso-150	864.67	131829.65	21282	519.44 %	0	131829.65	131829.65
	pso-qpso-200	1103.96	134368.68	21282	531.37 %	0	134368.68	134368.68
	pso-qpso-50	277.62	139160.21	21282	553.89 %	0	139160.21	139160.21
	pso-spso-100	354.45	134263.78	21282	530.88 %	0	134263.78	134263.78
	pso-spso-150	561.76	131779.46	21282	519.21 %	0	131779.46	131779.46
	pso-spso-200	711.47	137308.3	21282	545.19 %	0	137308.3	137308.3
	pso-spso-50	178.64	135109.1	21282	534.85 %	0	135109.1	135109.1
	two_opt	41.3	25201.01	21282	18.41 %	1194.06	22343.74	29121.31
kroC100	aco-100	4434.21	24984.31	20749	20.41 %	684.99	22754.14	25951.33
	aco-50	2223	25403.7	20749	22.43 %	637.92	23547.99	27133.87
	f_inc_loop	0.19	22610.52	20749	8.97 %	545.06	21513.14	24348.71
	inc_loop	0.43	24422.8	20749	17.71 %	828.53	22166.36	26078.16
	opt_greedy	17.42	23566.4	20749	13.58 %	0	23566.4	23566.4

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TABLE VI – continued from previous page

TSP	Algorithm	Time (s)	Avg.Dist.	Opt.Dist.	%	σ	MIN	MAX
	pso-apso-100	374.74	133001.54	20749	541 %	0	133001.54	133001.54
	pso-apso-150	599.83	131645.92	20749	534.47 %	0	131645.92	131645.92
	pso-apso-200	775.41	133489.43	20749	543.35 %	0	133489.43	133489.43
	pso-apso-50	188.68	136689.97	20749	558.78 %	0	136689.97	136689.97
	pso-qpso-100	550.94	130673.46	20749	529.78 %	0	130673.46	130673.46
	pso-qpso-150	863.69	134922.05	20749	550.26 %	0	134922.05	134922.05
	pso-qpso-200	1097.33	131269.53	20749	532.65 %	0	131269.53	131269.53
	pso-qpso-50	279.65	135164.95	20749	551.43 %	0	135164.95	135164.95
	pso-spso-100	350.78	130080.84	20749	526.93 %	0	130080.84	130080.84
	pso-spso-150	571.93	129039.17	20749	521.91 %	0	129039.17	129039.17
	pso-spso-200	709.37	124951.8	20749	502.21 %	0	124951.8	124951.8
	pso-spso-50	182.69	133891.02	20749	545.29 %	0	133891.02	133891.02
	two_opt	33.3	24849.14	20749	19.76 %	1413.94	22629	29718.89
kroD100	aco-100	4451.49	25641.03	21294	20.41 %	476.75	23999.45	26631.65
	aco-50	2240.22	26022.22	21294	22.2 %	599.74	24338.08	27116.16
	f_inc_loop	0.18	23175.24	21294	8.83 %	573.39	21841.78	24401.49
	inc_loop	0.46	24710.22	21294	16.04 %	701.77	23114.38	26320.06
	opt_greedy	10.84	24855.8	21294	16.73 %	0	24855.8	24855.8
	pso-apso-100	371.94	127502.35	21294	498.77 %	0	127502.35	127502.35
	pso-apso-150	611.6	125672.57	21294	490.18 %	0	125672.57	125672.57
	pso-apso-200	768.38	130238	21294	511.62 %	0	130238	130238
	pso-apso-50	190.9	133933.6	21294	528.97 %	0	133933.6	133933.6
	pso-qpso-100	547.1	131597.48	21294	518 %	0	131597.48	131597.48
	pso-qpso-150	865.49	128980.2	21294	505.71 %	0	128980.2	128980.2
	pso-qpso-200	1111.38	129555.11	21294	508.41 %	0	129555.11	129555.11
	pso-qpso-50	274.26	134102.64	21294	529.77 %	0	134102.64	134102.64
	pso-spso-100	350.95	125075.13	21294	487.37 %	0	125075.13	125075.13
	pso-spso-150	568.05	126403.57	21294	493.61 %	0	126403.57	126403.57
	pso-spso-200	717.92	129221.76	21294	506.85 %	0	129221.76	129221.76
	pso-spso-50	184.94	121535.63	21294	470.75 %	0	121535.63	121535.63
	two_opt	32.88	24924.59	21294	17.05 %	1041.19	23129.67	28389.74
lin105	aco-100	4657.74	16749.66	14379	16.49 %	419.39	15596.34	17633.8
	aco-50	2360.69	17060.06	14379	18.65 %	477.18	15640.59	18206.24
	f_inc_loop	0.18	15860.13	14379	10.3 %	396.47	14840.72	17018.1
	inc_loop	0.51	17022.58	14379	18.39 %	560.86	15828.34	18201.03
	opt_greedy	11.56	16939.44	14379	17.81 %	0	16939.44	16939.44
	pso-apso-100	379.52	80167.92	14379	457.53 %	0	80167.92	80167.92
	pso-apso-150	617.98	71804.99	14379	399.37 %	0	71804.99	71804.99
	pso-apso-200	784.18	68635.69	14379	377.33 %	0	68635.69	68635.69
	pso-apso-50	193.53	74089.44	14379	415.26 %	0	74089.44	74089.44
	pso-qpso-100	553.75	56150.42	14379	290.5 %	0	56150.42	56150.42
	pso-qpso-150	873.59	48541.49	14379	237.59 %	0	48541.49	48541.49
	pso-qpso-200	1116.07	46208.14	14379	221.36 %	0	46208.14	46208.14
	pso-qpso-50	282.37	53148.22	14379	269.62 %	0	53148.22	53148.22
	pso-spso-100	360.95	66070.67	14379	359.49 %	0	66070.67	66070.67
	pso-spso-150	577.7	63343.04	14379	340.52 %	0	63343.04	63343.04
	pso-spso-200	719.67	57616.65	14379	300.7 %	0	57616.65	57616.65
	pso-spso-50	184.95	65117.8	14379	352.87 %	0	65117.8	65117.8
	two_opt	18.8	17240.81	14379	19.9 %	840.76	15557.94	20008.42
pr1002	aco-100	89526.28	453823.16	259045	75.19 %	6034.46	432512.18	463697.73
	aco-50	44797.11	482237.11	259045	86.16 %	7478.98	453680.83	495023.6

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TABLE VI – continued from previous page

TSP	Algorithm	Time (s)	Avg.Dist.	Opt.Dist.	%	σ	MIN	MAX
	f_inc_loop	8.56	292135.23	259045	12.77 %	2558.52	285620.02	298310.16
	inc_loop	388.55	301216.88	259045	16.28 %	2574.58	293699.67	309751.06
	opt_greedy	5525.38	312237.27	259045	20.53 %	0	312237.27	312237.27
	pso-apso-100	1987.77	5586377.93	259045	2056.53 %	0	5586377.93	5586377.93
	pso-apso-150	3022.24	5746239.95	259045	2118.24 %	0	5746239.95	5746239.95
	pso-apso-200	4078.99	5489574.44	259045	2019.16 %	0.11	5489574.44	5489574.44
	pso-apso-50	1020.95	5700604.23	259045	2100.62 %	0	5700604.23	5700604.23
	pso-qpso-100	2138.59	4654134.94	259045	1696.65 %	0	4654134.94	4654134.94
	pso-qpso-150	3153.35	4445011.54	259045	1615.92 %	0	4445011.54	4445011.54
	pso-qpso-200	4179.51	4381837.86	259045	1591.54 %	0	4381837.86	4381837.86
	pso-qpso-50	1083.76	4808843.31	259045	1756.37 %	0	4808843.31	4808843.31
	pso-spso-100	1773.51	5204886.62	259045	1909.26 %	0	5204886.62	5204886.62
	pso-spso-150	2534	4969495.03	259045	1818.39 %	0	4969495.03	4969495.03
	pso-spso-200	3326.83	5089123.89	259045	1864.57 %	0.06	5089123.89	5089123.89
	pso-spso-50	852.6	5304721.91	259045	1947.8 %	0.06	5304721.91	5304721.91
	two_opt	926.25	348246.58	259045	34.43 %	2346.38	333308.81	349438.24
pr2392	aco-100	414119.86	758803.69	378032	100.72 %	9151.06	735453.04	777169.14
	aco-50	211499.52	828058.08	378032	119.04 %	10575.98	791295.71	845482.94
	f_inc_loop	47.55	437608.45	378032	15.76 %	2804.39	430651.73	444002.51
	inc_loop	5416.46	455999.14	378032	20.62 %	2151.88	451372.65	460240.09
	opt_greedy	81904.36	458789.65	378032	21.36 %	0	458789.65	458789.65
	pso-apso-100	4868.08	13887665.42	378032	3573.67 %	0	13887665.42	13887665.42
	pso-apso-150	9406.84	13529590.85	378032	3478.95 %	0	13529590.85	13529590.85
	pso-apso-200	18280.38	13621714.24	378032	3503.32 %	0.18	13621714.24	13621714.24
	pso-apso-50	2336.25	13655832.79	378032	3512.35 %	0	13655832.79	13655832.79
	pso-qpso-100	6082.04	12739768.37	378032	3270.02 %	0	12739768.37	12739768.37
	pso-qpso-150	9554.1	12585053.92	378032	3229.1 %	0	12585053.92	12585053.92
	pso-qpso-200	12217.4	12023185.53	378032	3080.47 %	0.18	12023185.53	12023185.53
	pso-qpso-50	3046.98	12769142.91	378032	3277.79 %	0.18	12769142.91	12769142.91
	pso-spso-100	4154.98	13204005.65	378032	3392.83 %	0	13204005.65	13204005.65
	pso-spso-150	6269.83	13126757.49	378032	3372.39 %	0	13126757.49	13126757.49
	pso-spso-200	8176.07	13098856.98	378032	3365.01 %	0.18	13098856.98	13098856.98
	pso-spso-50	2105.91	13605994.73	378032	3499.16 %	0	13605994.73	13605994.73
	two_opt	22.61	378062.83	378032	0.01 %	0	378062.83	378062.83
pr76	aco-100	3279.6	122719.12	108159	13.46 %	2202.63	117488.89	127056.17
	aco-50	1655.52	124151.94	108159	14.79 %	2321.81	117472.06	129675.58
	f_inc_loop	0.13	116023.25	108159	7.27 %	3190.49	109616.78	124466.13
	inc_loop	0.28	122439.77	108159	13.2 %	3729.23	114185.6	130647.45
	opt_greedy	5.75	130921	108159	21.04 %	0	130921	130921
	pso-apso-100	341.23	314295.21	108159	190.59 %	0	314295.21	314295.21
	pso-apso-150	549.17	359030.08	108159	231.95 %	0	359030.08	359030.08
	pso-apso-200	699.96	327419.29	108159	202.72 %	0	327419.29	327419.29
	pso-apso-50	171.06	346302.83	108159	220.18 %	0	346302.83	346302.83
	pso-qpso-100	501.45	272633.24	108159	152.07 %	0	272633.24	272633.24
	pso-qpso-150	795.2	245483.68	108159	126.97 %	0	245483.68	245483.68
	pso-qpso-200	1026.5	227953.32	108159	110.76 %	0	227953.32	227953.32
	pso-qpso-50	257.89	290853.6	108159	168.91 %	0	290853.6	290853.6
	pso-spso-100	325.39	358624.29	108159	231.57 %	0	358624.29	358624.29
	pso-spso-150	520.93	316286.84	108159	192.43 %	0	316286.84	316286.84
	pso-spso-200	643.01	275485.24	108159	154.7 %	0	275485.24	275485.24
	pso-spso-50	163.27	385109.1	108159	256.06 %	0	385109.1	385109.1

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TABLE VI – continued from previous page

TSP	Algorithm	Time (s)	Avg.Dist.	Opt.Dist.	%	σ	MIN	MAX
	two_opt	3.27	129474.35	108159	19.71 %	6315.25	111934.95	145197.34
rd100	aco-100	4413.83	9891.62	7910	25.05 %	220.06	9143.86	10303.68
	aco-50	2214.92	10057.32	7910	27.15 %	249.66	9304.74	10568.33
	f_inc_loop	0.17	8678.43	7910	9.71 %	251.46	8002.19	9277.06
	inc_loop	0.44	9086.85	7910	14.88 %	213.52	8644.89	9587.05
	opt_greedy	10.47	9427.33	7910	19.18 %	0	9427.33	9427.33
	pso-apso-100	376.81	44275.44	7910	459.74 %	0	44275.44	44275.44
	pso-apso-150	614.56	44794.28	7910	466.3 %	0	44794.28	44794.28
	pso-apso-200	782.81	44151.65	7910	458.18 %	0	44151.65	44151.65
	pso-apso-50	192.2	41808.23	7910	428.55 %	0	41808.23	41808.23
	pso-qpso-100	551.61	45436	7910	474.41 %	0	45436	45436
	pso-qpso-150	864.81	45073.22	7910	469.83 %	0	45073.22	45073.22
	pso-qpso-200	1105.84	44698.95	7910	465.09 %	0	44698.95	44698.95
	pso-qpso-50	277.09	45519.16	7910	475.46 %	0	45519.16	45519.16
	pso-spso-100	349.83	43824.5	7910	454.04 %	0	43824.5	43824.5
	pso-spso-150	575.41	43306.23	7910	447.49 %	0	43306.23	43306.23
	pso-spso-200	702.75	45103.01	7910	470.2 %	0	45103.01	45103.01
	pso-spso-50	179.39	45100.51	7910	470.17 %	0	45100.51	45100.51
	two_opt	30.05	9440.72	7910	19.35 %	364.27	8673.3	10555.51
st70	aco-100	3025.84	797.13	675	18.09 %	16.15	758.22	824.25
	aco-50	1508.22	808.84	675	19.83 %	18.69	763.21	846.03
	f_inc_loop	0.11	724.52	675	7.34 %	17.78	694.17	771.82
	inc_loop	0.22	755.21	675	11.88 %	23.75	709.41	808.62
	opt_greedy	4.53	761.69	675	12.84 %	0	761.69	761.69
	pso-apso-100	330.51	2480.57	675	267.49 %	0	2480.57	2480.57
	pso-apso-150	544.94	2648.7	675	292.4 %	0	2648.7	2648.7
	pso-apso-200	681.68	2477.52	675	267.04 %	0	2477.52	2477.52
	pso-apso-50	166.9	2777.89	675	311.54 %	0	2777.89	2777.89
	pso-qpso-100	493.05	2879.27	675	326.56 %	0	2879.27	2879.27
	pso-qpso-150	789.01	2879.97	675	326.66 %	0	2879.97	2879.97
	pso-qpso-200	997.68	2910.58	675	331.2 %	0	2910.58	2910.58
	pso-qpso-50	249.33	2606.64	675	286.17 %	0	2606.64	2606.64
	pso-spso-100	315.58	2588.4	675	283.47 %	0	2588.4	2588.4
	pso-spso-150	479.46	2634.6	675	290.31 %	0	2634.6	2634.6
	pso-spso-200	640.64	2906.11	675	330.54 %	0	2906.11	2906.11
	pso-spso-50	159.09	2934.59	675	334.75 %	0	2934.59	2934.59
	two_opt	8.85	756.17	675	12.02 %	25.71	701.2	858.12
tsp225	aco-100	11119.3	5515.97	3916	40.86 %	117.03	5016.72	5697.63
	aco-50	5598.57	5705.96	3916	45.71 %	123.55	5382.33	5911.7
	f_inc_loop	0.53	4318.92	3916	10.29 %	76.34	4125.54	4485.59
	inc_loop	3.39	4465.02	3916	14.02 %	69.36	4261.54	4618.41
	opt_greedy	75.03	4633.2	3916	18.31 %	0	4633.2	4633.2
	pso-apso-100	542.21	32319.5	3916	725.32 %	0	32319.5	32319.5
	pso-apso-150	817.46	32476.42	3916	729.33 %	0	32476.42	32476.42
	pso-apso-200	1097.01	32595.68	3916	732.37 %	0	32595.68	32595.68
	pso-apso-50	278.4	33263.68	3916	749.43 %	0	33263.68	33263.68
	pso-qpso-100	754.71	24450.75	3916	524.38 %	0	24450.75	24450.75
	pso-qpso-150	1126.55	25324.44	3916	546.69 %	0	25324.44	25324.44
	pso-qpso-200	1503.28	23371.2	3916	496.81 %	0	23371.2	23371.2
	pso-qpso-50	382.82	25277.65	3916	545.5 %	0	25277.65	25277.65
	pso-spso-100	505.77	30930.42	3916	689.85 %	0	30930.42	30930.42

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TABLE VI – continued from previous page

TSP	Algorithm	Time (s)	Avg.Dist.	Opt.Dist.	%	σ	MIN	MAX
	pso-spso-150	743.16	28516.88	3916	628.21 %	0	28516.88	28516.88
	pso-spso-200	971.32	28788.59	3916	635.15 %	0	28788.59	28788.59
	pso-spso-50	257.34	31676.63	3916	708.9 %	0	31676.63	31676.63
	two_opt	316.7	5185.16	3916	32.41 %	291.15	4618.5	6149.86
ulysses16	aco-100	666.27	6860.24	6859	0.02 %	3.85	6859	6878
	aco-50	343.27	6870.7	6859	0.17 %	18.26	6859	6913
	f_inc_loop	0.03	7081.87	6859	3.25 %	170.32	6859	7562
	inc_loop	0.04	7320.39	6859	6.73 %	167.63	6909	7550
	opt_greedy	0.21	7943	6859	15.8 %	0	7943	7943
	pso-apso-100	267.36	7358	6859	7.28 %	0	7358	7358
	pso-apso-150	412.45	6952	6859	1.36 %	0	6952	6952
	pso-apso-200	539.71	7428	6859	8.3 %	0	7428	7428
	pso-apso-50	134.32	7381	6859	7.61 %	0	7381	7381
	pso-qpso-100	404.97	7285	6859	6.21 %	0	7285	7285
	pso-qpso-150	629.87	6950	6859	1.33 %	0	6950	6950
	pso-qpso-200	841.98	7138	6859	4.07 %	0	7138	7138
	pso-qpso-50	203.9	7667	6859	11.78 %	0	7667	7667
	pso-spso-100	260.41	7289	6859	6.27 %	0	7289	7289
	pso-spso-150	395.96	7469	6859	8.89 %	0	7469	7469
	pso-spso-200	523.81	7256	6859	5.79 %	0	7256	7256
	pso-spso-50	131.64	8307	6859	21.11 %	0	8307	8307
	two_opt	0.41	6962.99	6859	1.52 %	99.51	6859	7196
ulysses22	aco-100	922.24	7066.48	7013	0.76 %	34.32	7013	7127
	aco-50	471.15	7088.49	7013	1.08 %	42.12	7013	7213
	f_inc_loop	0.04	7312.48	7013	4.27 %	178.35	7013	7714
	inc_loop	0.05	7613.18	7013	8.56 %	162.75	7128	8121
	opt_greedy	0.39	8180	7013	16.64 %	0	8180	8180
	pso-apso-100	279.78	9599	7013	36.87 %	0	9599	9599
	pso-apso-150	421.93	9074	7013	29.39 %	0	9074	9074
	pso-apso-200	554.91	9605	7013	36.96 %	0	9605	9605
	pso-apso-50	140.89	9580	7013	36.6 %	0	9580	9580
	pso-qpso-100	422.07	8562	7013	22.09 %	0	8562	8562
	pso-qpso-150	643.18	9137	7013	30.29 %	0	9137	9137
	pso-qpso-200	852.69	9319	7013	32.88 %	0	9319	9319
	pso-qpso-50	212.05	8261	7013	17.8 %	0	8261	8261
	pso-spso-100	270.91	9480	7013	35.18 %	0	9480	9480
	pso-spso-150	405.16	8447	7013	20.45 %	0	8447	8447
	pso-spso-200	537.29	8454	7013	20.55 %	0	8454	8454
	pso-spso-50	135.97	9125	7013	30.12 %	0	9125	9125
	two_opt	0.59	7176.22	7013	2.33 %	102.41	7013	7441

TABLE VI: Performance Summary

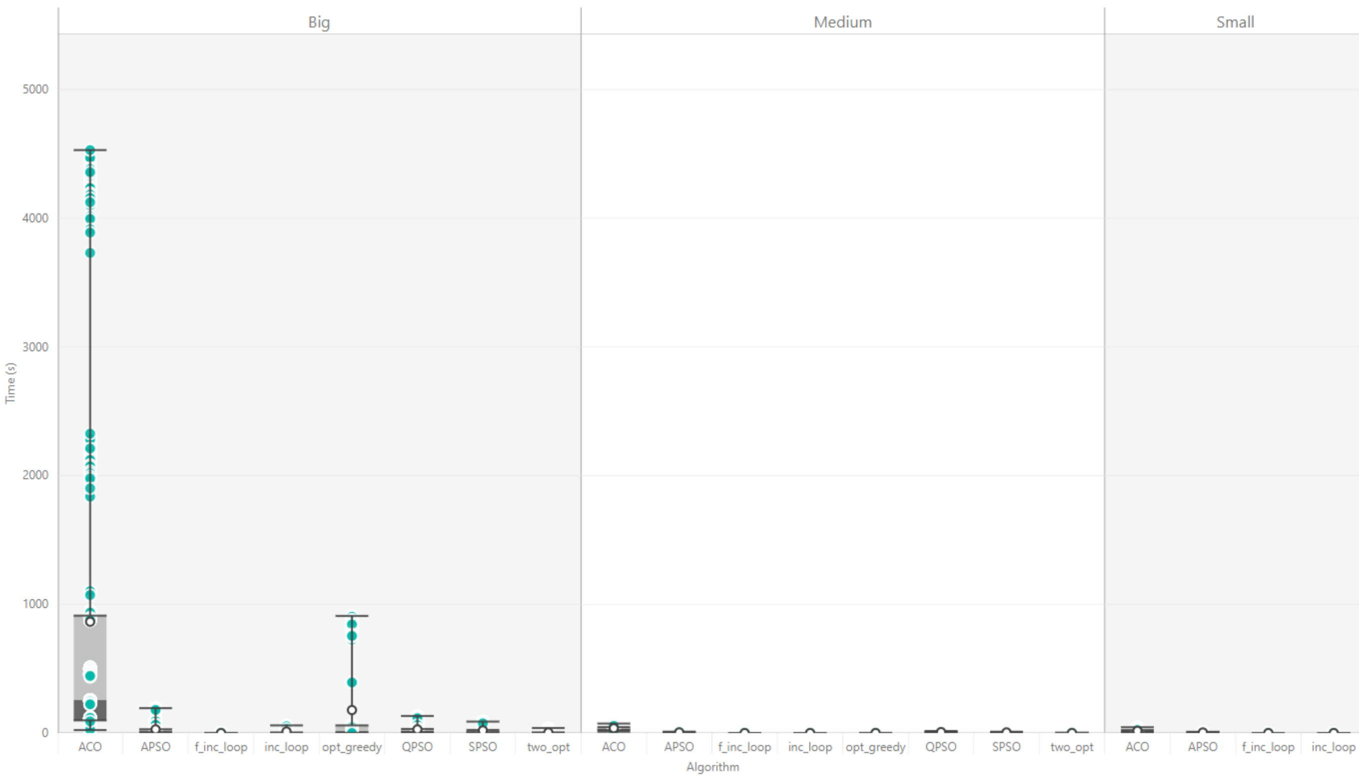

Fig. 8. Computation Time of each algorithm based on the TSP classification