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An Hybrid Metaheuristic Approach to the Travelling Salesman Problem

Authors:

Dario Bertazioli - 847761 - d.bertazioli@campus.unimib.it
Fabrizio D'Intinosante - 838866 - f.dintinosante@campus.unimib.it
Massimiliano Perletti - 847548 - m.perletti2@campus.unimib.it

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Abstract

The ABSTRACT is not a part of the body of the report itself. Rather, the abstract is a brief summary of the report contents that is often separately circulated so potential readers can decide whether to read the report. The abstract should very concisely summarize the whole report: why it was written, what was discovered or developed, and what is claimed to be the significance of the effort. The abstract does not include figures or tables, and only the most significant numerical values or results should be given. The ABSTRACT is not a part of the body of the report itself. Rather, the abstract is a brief summary of the report contents that is often separately circulated so potential readers can decide whether to read the report. The abstract should very concisely summarize the whole report: why it was written, what was discovered or developed, and what is claimed to be the significance of the effort. The abstract does not include figures or tables, and only the most significant numerical values or results should be given.

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1 Introduction

The problem: the travelling salesman problem (TSP) is an algorithmic problem tasked with finding the shortest route between a set of points and locations that must be visited. In the problem statement, the points are the cities a salesperson might visit. The salesman’s goal is to keep the distance travelled as low as possible. TSP has been studied for decades and several solutions have been theorized. The simplest solution is to try all possibilities, but this is also the most time consuming and expensive method. Many solutions use heuristics, which provides probability outcomes. It must be considered that the results are approximate and not always optimal.

Our approach: in this project we tried to apply two meta-heuristics named *Ant Colony Optimization* and *Genetic Algorithm*, implementing their "classical" version and a custom one integrating *Reinforcement Learning Algorithm*, namely *Q-learning* and *Clustering algorithm*, in particular *K-Means* respectively for the first and the second one.

1.1 Ant Family Algorithms

In this work we focus on two different approaches to the TSP: implementing some algorithms of the "Ant-type" family, and some Evolutionary Algorithms.

The former approach is based on the exploitation of a set of algorithms called "Ant-Family".

1.1.1 Ant Colony Optimization

The first type of "Ant-like" algorithm we implement is the **Ant Colony Optimization** (ACO) algorithm.

The procedure draws inspiration from a "real" Ant Colony. In nature, such a system is known to accomplish some difficult tasks, being beyond the capabilities of a single ant, exploiting the individuals collaborating with each other.

In particular, ACO algorithm is based on foraging behaviour of some ant species. This behaviour can be summed up as their ability to find the shortest paths between a source of food and their nest. The cooperation among the ants has inspired researchers to apply a similar collaboration based algorithm to those problems whose solutions can be formulated as a least cost path between an origin and a destination. Since most optimisation problems might have such a formulation, those kind of algorithms are pretty interesting.

The first ACO algorithm, Ant System, was proposed by Dorigo [2, 3, 4, 5, 6].

It consists in a **multi-agent** approach that can produce good-quality solutions in a reasonable time for combinatorial optimisation problems [2]. The author demonstrate the performance of this algorithm on Travelling Salesman Problem (TSP) [3].

Regarding the basic mechanism of ACO, here follows a quick biological explanation. Ant species are almost blind, thus they interact with the environment and communicate with each other exploiting the hormones they release. In particular some ant species use a special kind of hormone called **pheromone**: they lay pheromone trails on the paths they explore, these traces act as stimuli and other ants belonging to the colony are attracted to follow the paths that have relatively more tracked. Due to this mechanism, an individual who is following a path because of the pheromone trail also reinforces it by dropping its own pheromone too.

Thus, the more ants follow a specific path, the more likely that path becomes to be followed by the ants in the colony [2, 5, 6].

ACO algorithm makes use of ant-like agents called **artificial ants**, that construct their solutions collaboratively by sharing their experience on the quality of solutions that were generated so far. The pheromone trails play a leading role in the utilization of collective experience. The solutions are built iteratively. Artificial ants store the path they followed while constructing their solutions. Exploiting such a memory, typically (even though depending on the specific class of ant colony algorithm) artificial

ants do not deposit the pheromone until they have constructed their solution. Then, They determine the amount of pheromone according to the quality of their solution and upload the pheromone matrix (the data structure in which the pheromone amount for each part of the total path is stored). Automatically, the paths belonging to better solutions, receive more pheromone.

In iteratively building a solution (a total path) for a single ant, a local stochastic transition policy is typically applied, establishing how to decide the next node to visit in a graph. Artificial ants make their decisions and transitions to their next state in discrete time steps, deciding whether to follow the main trails, or to random explore a new path (in our implementation, such a decision is made by a random number generation and imposing a threshold). Exploration is also encouraged by a mechanism of pheromone evaporation, which prevents the colony from getting stuck into a solution corresponding to a (only) local optimum (note however that in real ant colonies pheromone evaporation is too slow to be a significant part of their search mechanism).

1.1.2 Ant-Q Metaheuristic

In order to better understanding the working mechanism of Ant-Q Metaheuristic and to give deeper insight in our implentation (following [7]), let us introduce some theoretical hints for the context.

Hints on reinforcement learning: Reinforcement Learning (RL) is an (almost) unsupervised learning approach.

It consists of an **agent** who tries to learn how to reach a goal by a continuous interaction with the environment. There is an evaluation phase where the quality of agent's actions is considered and feedbacks to the agent are given in the form a numerical reward. This type of feedback is known as evaluative feedback: in contrary of supervised learning, here the agent is not explicitly told what action is the best to take in a certain situation, whereas it should try a set of possible actions and learn the best strategy yielding the most reward itself.

In some cases, the goal state (that is, the agent reaching its objective) can be obtained only after a sequence of actions: as a result the reward is delayed (this particular feature will be a central part of the implementation that will be presented later in Eq.14).

Summing up, and according to [8], the RL problem can be defined as the problem of an agent interacting with a complex environment trying to maximise its long-run reward over a sequence of discrete time steps.

The agent follows a **policy** to decide on its action according to the current state and conditions.

This policy is typically a stochastic function ($\pi(s, a)$) that indicates a probability of choosing an action a given a state s . Notice that agent has the possibility to change its initial policy according to new experiences in order to achieve optimal cumulative reward over time.

The value of a state $V_\pi(s)$ is defined as the expected cumulative reward that will be obtained starting from a state s and acting according to the current policy π . In the same way, the value of a pair state-action($Q_\pi(s, a)$) is the expected return obtained starting from s with action a and then following the policy. In formulas, V is defined as:

$$V^\pi(s) = E_\pi \left\{ \sum_i \gamma^i r_{t+1, i+1} \mid s_t = s \right\} , \quad (1)$$

and accordingly:

$$Q^\pi(s, a) = E_\pi \left\{ \sum_i \gamma^i r_{t+1, i+1} \mid s_t = s, a_t = a \right\} . \quad (2)$$

The RL problem consists in the agent trying to find the optimal policy π^* that maximizes the value functions, obtaining thus:

$$V^*(s) = \max_{a \in A(s)} (Q^{\pi^*}(s, a)) . \quad (3)$$

However, the policy estimation can be in general a complex problem, and an optimal policy can be obtained with various algorithms, such as Policy Iteration and Value Iteration. There are also kind of learning mechanism defined as “off-policy”, because they do not exploit a proper policy procedure.

```

Randomly initialise  $Q(s, a)$ 
Repeat for each episode
  Initialise the current state  $s$ 
  While  $s$  is not terminal state
    Choose action  $a$  at the current state  $s$  according to the policy (e.g.  $\epsilon$ -greedy)
    Take action  $a$ , observe reward  $r$  and next state  $s'$ 
     $Q(s, a) \leftarrow Q(s, a) + \alpha[r + \gamma \max_{a'} Q(s', a') - Q(s, a)]$ 
     $s \leftarrow s'$ 

```

Figure 1: The pseudo code of a typical Q-learning algorithm implementation.

Q-Learning : is an off-policy method, meaning that it updates the values iteratively basing this process on the action that gives the maximum value (that is, such an algorithm tries to directly learn Q^* instead of learning Q_π first). In figure 1 it is shown the pseudocode of the algorithm: the agent uses a so called ϵ -greedy policy, but updating the current value estimate considering the action that provides the maximum value at the successor state instead of considering the (current-)policy-suggested action.

Ant-Q Algorithm : one of the core points of this project consists in the implementation of the Ant-Q algorithm, introduced by Gambardella [7] in collaboration with Dorigo, attempting to ameliorate the “classic” ACO performances.

In this approach, the pheromone update rule is borrowed from the Q-learning praxis:

$$Q(s, a) \leftarrow (1 - \alpha)Q(s, a) + \alpha(r + \gamma[\max_{a'} Q(s', a') - Q(s, a)]) . \quad (4)$$

Thus, the Ant-Q algorithm is a crossover between a “simple” Ant Colony algorithm and a Q-learning algorithm. The basic structure belongs to the Ant family, whereas the update rule as well as the decision schedule for exploring the nodes (that is, the modality an artificial ant selects the next node to visit, starting from a given node) is imported from the cited reinforcement learning algorithm.

1.2 Evolutionary Algorithms

1.2.1 Genetic Algorithm

The latter approach we faced along this work is the **Genetic Algorithm** (GA), which we initially implement in its classical version. This algorithm is based on a biological metaphor: the resolution of a problem is seen as a competition among a population whose evolving individuals become better and better candidates solutions over time. A “fitness” function is used to evaluate each individual to decide whether it will contribute to the next generation. Then, in analogy with the biological metaphor (the gene transfer in sexual reproduction), a crossover operator is applied in order to generate the next generation of the population. This process, according to the evolutionary theory (Darwinism), should lead after a certain number of iterations to a much more fit ensemble of individuals representing “good” candidate solutions to the considered problem.

1.2.2 K-Means GA Metaheuristic

With the aim to improve classic GA performance on big dataset, different hybridization techniques have been created. One of these consist in splitting the main problem in multiple sub-problems, with reduced dimension, in order to reach an easier problem form. K-Means GA meta-heuristic (KGA) shortly consists in cluster the data using a simple clustering method, the K-Means method, apply the GA algorithm on every data cluster, with dimension smaller than the original total data dimension and

finally rebuild the final solution starting from the smaller multiple solutions. The K-Means method is shortly described below.

Clustering with K-Means: At first, specifically for the TSP problem, we need to cluster our cities into close groups with a clustering method.

The *K-Means* method is designed to partition a set of data into K classes with K chosen as desired. This method constructs partitions of the data-matrix so that the squared Euclidean distance between the row vector for any object and the centroid vector of its respective cluster is at least as small as the distances to the centroids of the remaining clusters. The centroid of cluster C_k is a point in P -dimensional space found by averaging the values on each variable over the objects within the cluster. For instance, the centroid value for j -th variable in cluster C_k is

$$\bar{x}_j^{(k)} = \frac{1}{n_k} \sum_{i \in C_k} x_{ij} , \quad (5)$$

and the complete centroid vector for cluster C_k is given by [9]

$$\bar{x}^{(k)} = (\bar{x}_1^{(k)}, \bar{x}_2^{(k)}, \dots, \bar{x}_p^{(k)}) . \quad (6)$$

2 Datasets

The datasets used in this work are taken from <https://wwwproxy.iwr.uni-heidelberg.de/groups/comopt/software/TSPLIB95/tsp/>, a large source of TSP datasets largely cited in literature. There are datasets of variable dimension and for everyone is also available the optimal solution so that is possible for us to compare our results with the optimal one. Every solution is available at <https://wwwproxy.iwr.uni-heidelberg.de/groups/comopt/software/TSPLIB95/STSP.html>. Every dataset is composed by a list of “cities” with two coordinates points; the only preprocessing we apply is to compute a matrix containing the distance between every point and the other ones.

In particular we use 5 datasets of different dimension:

- dj38
- berlin52
- ch130
- d198
- pr1002

We have chosen these datasets because they are very used and largely cited in literature allowing us to compare our results with others.

3 The Methodological Approach

3.1 ACO

As introduced in Sec. (1.1.1), Ant Colony Optimisation is a meta-heuristic proposed to solve hard optimisation problems. The ACO meta-heuristic, from a high-level point of view, is composed of two main stages:

- Constructing the single ant solution: the artificial ants construct their solutions. The transition policy controls the ants’ next step to one of the adjacent nodes. Once the ants have completed their path, the quality of the current solution is evaluated, and used in the next step. The decision policy is based on following a probability distribution of the type [2]:

$$p_{ij}^k = \frac{[\tau_{ij}]^\alpha [\eta_{ij}]^\beta}{\sum_{l \in N_i^k} [\tau_{il}]^\alpha [\eta_{il}]^\beta} \quad \text{if } j \in N_i^k, \quad (7)$$

where

- η_{ij} indicates an heuristic value specified according to the problem; in the TSP case, we considered it to be $1/d_{ij}$, coherently with the choice of [2].
- τ_{ij} is the pheromone quantity on the path between the i -th and j -th nodes,
- α and β are the parameters used to set the relative importance of the pheromone trail and the heuristic value. In our implementation, we attempted to change the values of those parameters in order to explore a set of possible configurations. We experienced that:
 - * as $\alpha \rightarrow 0$, the pheromone track become less important and the ants tend to choose the closest cities, resulting in a much more “greedy” search;
 - * vice-versa, when $\beta \rightarrow 0$, heuristic values are almost ignored and only the tracks are considered in the decision making;

From the little experience we made, it seems quite worth to notice that the optimal setting of those parameters depends on the particular dataset. More in details it might depend on the considered dimension and on the variance associated to the average distance between all the nodes: indeed, with small datasets (let us say having $n \leq 30$ nodes or less) the ACO seems to better perform when more importance is given on the pheromone effect, since the artificial ants quickly converges to a unique path (thus $\alpha \geq \beta$), whereas whenever a large dataset is considered the pheromone action of guiding artificial ants in their exploration seems to be as relevant as the heuristic value weight, resulting with a optimal configuration being a compromise between those actions (thus it might be better to have $\alpha \sim \beta$).

In the presented results α , β are fixed and equals to their most stable values taken from the literature (mostly from [2, 3], but): $\alpha = 1$ and $\beta = 3$.

- Update the pheromone matrix: the pheromone trails are adjusted based on the latest iteration of the colony search process. Two different updates happen:
 - the pheromone evaporates according to the equation:

$$\tau_{ij} = (1 - \rho)\tau_{ij}, \quad (8)$$

where ρ is the evaporation coefficient. In our implementation, and following the literature, ρ is taken equal to 0.9,

- new pheromone is deposited on the followed path. The amount of pheromone to deposit is typically decided according to the quality of the particular solutions that each path belongs to:

$$\Delta\tau_{ij} = \sum_{k=1}^m \Delta\tau_{ij}^k, \quad (9)$$

where $\Delta\tau_{ij}^k$ is the pheromone increase amount deposited by the k -th ant, which can be (e.g. in Dorigo initial work) taken either as a constant, or $\Delta\tau_{ij}^k = 1/L_k$, where L_k is the k -th ant path length.

However the entity of pheromone update and it's weight on how the search will be biased towards the best solution found so far is an implementation decision.

Note that the summation is extended up to a parameter m representing the number of artificial ants. The value of this parameter is taken to be $m = 4n$ with n being the number

Algorithm Ant Colony Optimization

Main Algorithm

```
0: initialize best_dist and best_path to None
1: for generation in generations:
2:   create n_ants artificial ants
3:   for one_ant in ants:
4:     make a single ant path (see Make path)
5:     compute the path length
6:     update best_dist and best_path
7:   update the pheromone matrix
   (local update only for child processes, according to Eq. (10))
8:   every a certain n of iterations:
9:     update the global pheromone matrix
   (shared in MPI environment among master&child.)
10: return best_dist, best_sol
```

Make path

```
1: start from a vertex
2: add start vertex to visited nodes
3: for each remaining vertex:
4:   list the neighbours
5:   list the not yet visited neighb
6:   calculate the probability of choosing a vertex (according to Eq. (7))
7:   choose the vertex according to probability
8:   add the chosen vertex to the visited list
9:   return the chosen vertex id
```

Local update pheromone matrix

```
1: for ant in ant_colony :
2:   for each vertex of one_ant_path :
3:     increase pheromone_matrix between current and next vertex of  $\Delta\tau$ 
   (according to Eq. (10))
```

Global update pheromone matrix (parallelism)

```
1: gather from MPI env all the pheromone matrices
2: if process is the parent process (rank==0):
3:   for each element average over the n_cores matrices.
4: broadcast obtained pheromone matrix to the other
   processes
```

Table 1: Ant Colony pseudocode

of nodes in the graph. This particular value is a completely experimental value, differing from the classical literature value being $m_{literature} = n$. The explanation of such a choice can be found in paragraph 3.2, being related to the parallel implementation.

– the following equations can be combined in:

$$\tau_{ij} = (1 - \rho)\tau_{ij} + \Delta\tau_{ij} . \quad (10)$$

The pseudocode of the ACO solution is presented in Tab. 1.

3.2 Ant-Q

In this subsection some more details, with respect to what anticipated in Sec. 1.1.2, will be given, and the implementation of the Ant-Q algorithm will be discussed. As it was previously stated, Ant-Q borrows the update rule from the Q-learning algorithm. Thus, Eq. (10) changes as the following:

$$\tau_{ij} = (1 - \alpha)\tau_{ij} + \alpha(\Delta\tau_{ij} + \gamma \max_{l \in N_j^k} \tau_{jl}) , \quad (11)$$

where *alpha* has a role similar to the previous evaporation coefficient ρ , and γ is the well-known parameter called in RL literature discount rate. In literature, in particular in [7] the typical choice of

such parameters is $\alpha = 0.1$ and $\gamma = 0.3$. We adopted this value for *alpha*, whereas we found to be a better choice for our implementation the $\gamma \rightarrow 1$. The better performance of the $\gamma = 1$ value in our case might be related to the parallel implementation, as further explained in 3.2.

The next action (what next node connecting to) is chosen according to:

$$s = \begin{cases} \arg \max_{a \in J_k(s)} [Q(s, a)]^\alpha [\eta(s, a)]^\beta & \text{if } q \leq q_0 \\ S & \text{otherwise} \end{cases}, \quad (12)$$

where, correspondingly to Eq. (7), η is an heuristic value associated to the inverse of distance between a pair of nodes, and α, β are parameters for the relative importance of pheromone effects (given by $Q \approx \tau$) and the distance measure (indeed $\eta \sim 1/d$).

Observing Eq. (11) in relation to the Q-learning update rule Eq. (4), we underline how much similar the Ant-Q pheromone matrix is compared to a “standard” Q table. Indeed, it is worth to notice that:

- Eq. (11) updates the pheromone value of the transition (i, j) according to the pheromone value of the next transition (j, l) ,
- Eq. (11) uses the second part of Eq. (4) (known as TD Error) to weight the pheromone quantity associated to the current edge with a learning rate α and a discount rate γ ,
- the equation

$$\tau_{ij} = (1 - \alpha)\tau_{ij} + \alpha(\gamma \max_{l \in N_j^k} \tau_{jl}), \quad (13)$$

is used for the pheromone matrix update (namely a local update) during each path construction (of each ant), and it does not include the delayed reward $\Delta\tau_{ij}$,

- $\Delta\tau_{ij}$ is calculated according to the solution quality, as anticipated circa Eq. (9), and assigned in a “delayed” mode: thus the value of $\Delta\tau_{ij}$ for all i and j will be 0 while the ants apply the update rule Eq. (13) during their construction of the current solution. Therefore, the update rule Eq. (11) is reapplied at the completion of the current solution, but with the value of the next transition considered to be equal to zero. (thus uploading only with $\Delta\tau_{ij}$:

$$\tau_{ij} = (1 - \alpha)\tau_{ij} + \alpha(\Delta\tau_{ij}), \quad (14)$$

- still according to [7] [8] $\Delta\tau_{ij}$ can be updated with an iteration best rule (update every single colony iteration) or global best (update based on the global best value).

Notice that many other attempts were made in the direction of hybridizing ACO and reinforcement learning based algorithms, some particularly interesting and successful, such as [10],[11],[12]. However, due to the few time available, we could head our force in implementing only the in-detail-described Ant-Q.

The pseudocode regarding our implementation of such an hybrid meta-heuristic is reported in Tab. 2

Parallel Implementation: since both the ACO and Ant-Q are memory and computational-expensive, we suggest a parallel implementation of each algorithm.

The type of proposed algorithm is naturally easy to code in a parallel implementation, being enough to split the total number of ants into a number of sets (called *n_ants_per_core* in the code) of ants that will be distributed on each single core.

Thus, a parent process initializes the algorithm, creating *n_core* children each operating on a “personal” memory area. Thus, every child has its own data structures, in particular its own pheromone matrix. The MPI/OpenMPI^{1 2} software (in particular mpi4py³, a pythonic Api for OpenMPI) is used

¹<https://www.open-mpi.org/>

²a nice introduction to MPI basic usage: https://princetonuniversity.github.io/PUbootcamp/sessions/parallel-programming/Intro_PP_bootcamp_2018.pdf

³<https://mpi4py.readthedocs.io/en/stable/>

Algorithm Ant-Q algorithm

Main Algorithm

```
0: initialize best_dist and best_path to None
1: for generation in generations:
2:   create n_ants artificial ants
3:   for each ant:
4:     make a single ant path (see Make path)
5:     compute the path length
6:     update best_dist and best_path
7:     update pheromone matrix with delayed rewards
      (according to Eq. (14))
8:   update the global pheromone matrix
      (shared in MPI environment among master&child.)
9: return best_dist, best_sol
```

Make path

```
1: start from a vertex
2: add start vertex to visited nodes
3: for each remaining vertex:
4:   list the neighbours
5:   list the not yet visited neighb
6:   generate a random number  $q \in \{0, 1\}$ 
7:   if  $q < q_0$ : (threshold)
8:     select next vertex according to Eq. (12)
9:   else:
10:    calculate the probability of choosing a vertex
11:    (according to Eq. (7))
12:    choose the vertex according to probability
13:    add the chosen vertex to the visited list
14:    give local rewards (local update pheromone matrix)
15:    return the chosen vertex id
```

Local update pheromone matrix

```
1: for ant in ant_colony :
2:   for each vertex of one_ant_path :
3:     increase pheromone_matrix between current
      and next vertex of a  $\Delta\tau$  (according to Eq. (11))
```

Global update pheromone matrix (parallelism)

```
1: gather from MPI env all the pheromone matrices
2: if process is the parent process (rank==0):
3:   for each element average over the n_cores matrices.
4: broadcast obtained pheromone matrix to the other
   processes
```

Table 2: Ant-Q pseudocode

to host a shared pheromone matrix which will be updated according to the pseudocode in Tab. 1,2 (as a mean-matrix), and which every “local” matrix will be update to after every iteration, so that every artificial ant in every child process will “feel” a as similar as possible pheromone effect.

As anticipated previously, we made slightly different choice in setting some parameters values:

- in both ACO and Ant-Q implementation, we take m , the number of ant agents, to be $m = n_{core} \times n$, where n is the number of nodes of the graph and n_{core} is the number of cores available for running parallel processes. This choice is explained due to the fact that in our implementation on each core one child (or the parent) process is running alone, and the initial amount of artificial ants is equally distributed among the cores. Every iteration the pheromone matrix created or locally updated by a process running a single core is globally updated and a pheromone mean matrix is calculated and shared among the other processes. Thus for each node the number of ants for each iteration is the classical $m_{single_core} = n$, because locally (while constructing the local pheromone matrix) the ant-ant interaction is the classical (and known in literature to be optimal) one;
- in Ant-Q, the parameter γ is taken to be equal or close to 1, differently from the main ref. [7]. This

Algorithm Genetic Algorithm

```
1: procedure Genetic(Tm, Tp, elite_n, Selection, MaxGen)
2:   Pop ← GeneratePopulation(Tp)
3:   Pop ← Evaluation(Pop)
4:   for i = 1 ... MaxGen do
5:     Pop ← Selection(elite_n from Pop)
6:     Pop ← Crossover(Pop)
7:     With probability Tm do:
8:       Pop ← Mutation(Pop)
9:   end for
10:  return the best solution in Pop
11: end procedure
```

Table 3: Genetic Algorithm pseudocode

choice is quite empirical, since we obtained slightly better performances with $\gamma \in [0.9, 1]$. For simplicity in producing the final results a value of $\gamma = 1$ is taken. A possible explanation of such a choice might be found once again in the parallel implementation: since the global pheromone matrix is the result of an average of the results of n_cores systems, the future choice taken considering such a matrix (having the role of a Q-table in this circumstances) might be more trustable with respect to the classical situation of a single system sequential implementation. Thus, if this is confirmed, a value of $\gamma \rightarrow 1$ would lead to a better performance.

3.3 GA

With reference to Sec. 1.2.1, the pseudo code of the standard genetic algorithm is summarized in the Tab. 3, where Tm is the mutation rate that determines the rate at which the mutation operator is applied, Tp is the population size (number of chromosomes), elite_n is the number of individuals selected with the Selection mechanism, based on the fitness function value, that have to be saved for the new generation without mutation in order to preserve good individuals and MaxG the number of generations used in the experiment[13]. The values for this parameters used in this implementation are discussed in Sec. 4.

Finally, with the aim to explore a new variation of the standard algorithm, we try to integrate a *Clustering algorithm* named *K-Means* in order to reduce the problem dimension and improve the genetic procedure performance.

As said evolutionary algorithms like *Genetic algorithm* uses operators inspired by natural selection such as reproduction, mutation, recombination and selection. *Genetic algorithm* is very customizable in every component; in this work we focus our attention on the selection part. In particular we try to apply the following selection strategies [14]:

- roulette-wheel selection;
- tournament selection.

The **roulette-wheel** selection consists in giving a weight to each chromosomes (the individuals in our population) and this weight corresponds to a portion of a roulette wheel. In this way chromosomes with higher fitness will have higher weight and a larger portion of the wheel

$$p_i = \frac{f_i}{\sum_{j=1}^n f_j} , \quad (15)$$

with f_i as the fitness value for the i th individual.

Algorithm K-Means Algorithm

- 1: Set the K cluster centers randomly;
 - 2: **repeat**
 - 3: **for** *each vertex* **do**
 - 4: Calculate distance measure to each cluster;
 - 5: Assign it to the closest cluster;
 - 6: **end**
 - 7: recompute the cluster centers positions;
 - 8: **until** stop criteria are met;
-

Table 4: K-Means pseudocode

Spinning the wheel for different times allows selecting the individuals for the next generation. Finally, the roulette wheel is nothing more than a weighted sort mechanism.

The **tournament** selection, instead, consists in randomly selecting a group of individuals from the larger population and taking only the one with the highest fitness. The number of individuals competing in each tournament is commonly set to 2 but in this work we decide to improve a variable tournament dimension for each iteration.

The other elements, however, are standard.

Among these we remember:

- **crossover:** we apply the simplest crossover strategy called *single-point*;
- **mutation:** we apply the simplest mutation version called *point mutation*, with a mutation probability described by a **mutation rate**.

The *single-point* crossover is one of the simple crossover technique used for random GA applications. This crossover uses the single point fragmentation of the parents and then combines the parents at the crossover point to create the offspring or child [15].

The *point mutation* consist in change each individual gene value according to a certain probability. The method is easy for operating, but it cannot effective control to mutation result [16].

Seeing the results in using the different selection techniques we decide to use *tournament* in classical GA and *roulette-wheel* in KGA. In fact the *roulette-wheel* selection implements more the exploitation aspects of GA while the *tournament* selection allow to improve a more exploratory approach, which is exactly what we need working on big permutations [17].

3.4 KGA

The **K-Means Genetic Algorithm** (KGA) as mentioned in Sec. 1.2.2, is composed by different phases described below.

K-Means Clustering: The first step consist of create an ordinary number of clusters using the K-Means clustering algorithm, which pseudocode is presented in Tab: 4.

Intra-group evolution operation: The aim of the intra-group evolution operation is to find the shortest path for the given vertices in each cluster. GA is performed in each cluster aiming to obtain an approximate solution by a couple of genetic operations like selection, crossover, and mutation. Running the GA algorithm on smaller portion of original data allows to improve performance and reach better solutions. Eventually all those clusters could be handled parallel. The result of this step is tours T_1, T_2, \dots, T_k for clusters C_1, C_2, \dots, C_k .

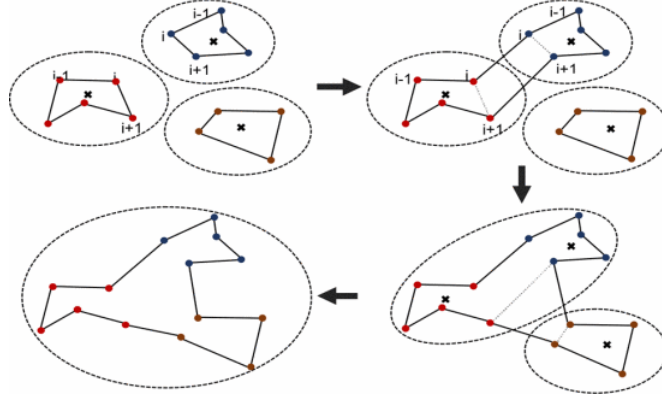


Figure 2: The inter-group connection procedure illustrated. Taken from [18].

Inter-group connection: In the last step, what we obtain is the shortest path between the given vertices in each cluster. With the aim to reconstruct the whole shortest path we need to connect properly every cluster to the others. Connect two clusters determine which edges will be deleted from the adjacent shortest path among each cluster, and which edges will be linked for combining two adjacent clusters into one. Assuming i and j are two closest vertices between two clusters G_i and G_j for G_i , $i-1$ and $i+1$ are two adjacent vertices of i , and the same to G_j , $j-1$ and $j+1$ are two adjacent vertices of j . Given G_i and G_j , in order to combine the two clusters into one, we need to select two vertices $i \in i'$ and $j \in j'$ for deleting and linking edges. With the aim to apply this strategy we refer to Eq. (16)

$$\{i^*, j^*\} = \operatorname{argmin}_{i', j'} \begin{cases} d_{ij} + d_{i'j'} - d_{ii'} - d_{jj'} \\ d_{ij'} + d_{i'j} - d_{ii'} - d_{jj'} \end{cases} \quad (16)$$

where $i' \in \{i-1; i+1\}$, $j' \in \{j-1; j+1\}$. Following this strategy, the first two clusters are combined into one, then the new generated cluster combines with the third cluster, and so on, step by step. At last, all those clusters are joined into one tour, and the shortest whole travelling tour is derived as shown in Fig. 2. The whole process of the KGA is listed in Tab. 5 [18],[19]. It is worth to underline that, in order to achieve better performance from the inter-group connection operation, we use the GA also to find the shortest path between the clusters *centroids*. This allow to improve the final result and restricts the number of intersections through the path.

4 Results and Evaluation

Each algorithm is tested on every dataset listed in Sec. (2). For every algorithm each run consists of five iterated executions, in order to compute the mean and standard deviation of the resulting optimal values.

The performance tests are executed on a machine with quad-core Intel(R) Xeon(R) CPU E5-2673 v4 @ 2.30GHz. Every parallel execution exploits all the four cores (thus, $n_cores = 4$).

Each table reported in this section also provide, for each run, the number of iterations for each algorithm, the best value, the averaged displacement (%) of each solution from the globally optimal value (OptimalTour)⁴, the percentage displacement (%) of the best solution found⁵, and the averaged cpu-time.

The average and best displacements are meant to be a sort of quality measure for the performances, whether the average time is taken into account as well.

⁴values taken from <https://wwwproxy.iwr.uni-heidelberg.de/groups/comopt/software/TSPLIB95/STSP.html>

⁵i.e. “% Best Dist” is calculated as % Best Dist = (OurBestSolution – OptimalTour)/OptimalTour * 100

Algorithm KGA

- 1: **input** an TSP;
 - 2: K-Means is adopted to cluster the TSP into k *sub-problems*
 - 3: **For** each sub-prob $i = 1$ to k , do:
 - 4: **repeat**
 - 5: GA procedure
 - 6: **until** *stop criteria are met*
 - 7: **Output** shortest path for sub-problem i ;
 - 8: **End**
 - 9: Seek for the best combining seq S with GA
 - 10: Combine all those shortest path into one tour
 - 11: **Output** the shortest whole travelling tour.
-

Table 5: KGA pseudocode

Tab. 6 presents the results of such a testing procedure for the ACO algorithm, whereas Tab. 7 provides the same information for the Ant-Q approach.

Dataset	ACO						
	OptimalTour	Mean	SD	Best	% Avg Dist	% Best Dist	Avg time (s)
dj38 (1000 it)	6656	6763.03	75.16	6708.04	1.61	0.78	75
berlin52 (1000 it)	7542	7925.39	162.00	7677.66	5.08	1.80	320
ch130 (500 it)	6110	6487.19	74.20	6385.46	6.17	4.51	9240
d198 (100 it)	15780	17376.23	105.81	17235.44	10.12	9.22	6540
pr1002 (10 it)	259054	337976.61	833.96	337309.96	30.47	30.21	6180

Table 6: The resulting ACO performances on the test datasets.

Dataset	Ant-Q						
	OptimalTour	Mean	SD	Best	% Avg Dist	% Best Dist	Avg time (s)
dj38 (1000 it)	6656	6663.99	4.16	6659.43	0.12	0.05	37
berlin52 (1000 it)	7542	7666.17	113.87	7548.99	1.65	0.09	170
ch130 (500 it)	6110	6491.31	70.01	6383.42	6.24	4.47	10200
d198 (100 it)	15780	17075.81	39.69	17032.75	8.21	7.94	2880
pr1002 (10 it)	259054						

Table 7: The resulting Ant-Q performances on the test datasets.

As regards the secondary part of this work, including GA and KGA, the following implementation details are provided:

- Keeping in mind Tab. 3, mutation rate (Tm), is typically set to $Tm = 0.01$. This choice is explained with the aim of limiting an excessive randomization while still maintaining a good trade-off between the exploitation and exploration behaviour.
- Population size (Tp) is set to $Tp = 300$ for every dataset with classic GA with the exception of *pr1002*, where the dataset dimension would have not allowed such a setting considering the computational limits. In this particular case we take $Tp = 125$. For each dataset used with KGA $Tp = 125$ considering the reduced dimensionality of the sub-problems which such an algorithm is applied to.

- Selection mechanism as mentioned in Sec. 3.3 is set to *tournament* in classic GA, and *roulette – wheel* in KGA.
- The action of elitism mechanism is controlled by a parameter, *elite_n*, corresponding to the number of individuals selected due to elitism, taken equal to 10% of *Tp* in most cases. In KGA *elite_n* is taken equal to 25.
- Number of generations (*MaxGen*) is set to *MaxGen* = 5000 in classic GA attempting to achieve a decent performance on such a large dataset. Instead, in KGA a larger value of *MaxGen* = 1000 is used for each dataset still considering the dimensional reduction associated with the clustering.
- Specifically for KGA algorithm, *k* is the number of clusters created with the K-Means algorithm in order to split the main problem into smaller sub-problems. In this implementation *k* is set to different values according to original problem’s dimension. In particular
 - *k* = 2 for dj38;
 - *k* = 3 for berlin52;
 - *k* = 8 for ch130;
 - *k* = 30 for d198;
 - *k* = 60 for pr1002.

The *k* dimensions are chose referring to the datasets’ points shape.

- it is worth to notice that KGA in addition to the number of generations into each cluster, has a number of iterations also to determine the optimal path between clusters’ centroids as mentioned in Sec. 1.2.2. This parameter is set to 1000 for each dataset regardless the clusters’ number. This is due to the will to equal compare the algorithm’s performance for each dataset.

Finally, Tab. 8 presents the results of such a testing procedure for the GA algorithm, whereas Tab. 9 provides the same information for the KGA approach.

Dataset	GA						
	OptimalTour	Mean	SD	Best	% Avg Dist	% Best Dist	Avg time (s)
dj38	6656	7032.91	574.34	6659.43	5.66	0.05	263
berlin52	7542	8095.35	167.27	7868.72	7.34	4.33	286
ch130	6110	7933.02	1041.27	6929.81	29.84	13.42	435
d198	15780	27579.73	1869.54	25537.85	74.78	61.84	604
pr1002	259045	4666413.09	12608.57	4652556.08	1701.39	1696.04	2641

Table 8: The resulting GA performances on the test datasets.

Dataset	KGA						
	OptimalTour	Mean	SD	Best	% Avg Dist	% Best Dist	Avg time (s)
dj38	6656	9608.77	1817.02	7720.03	44.36	15.99	140
berlin52	7542	8879.59	446.69	8218.95	17.74	8.98	188
ch130	6110	7790.85	312.17	7314.08	27.51	19.71	409
d198	15780	24023.86	3066.94	20830.94	52.24	32.01	1413
pr1002	259045	379495.87	6343.57	373865.26	46.50	44.32	4456

Table 9: The resulting KGA performances on the test datasets.

5 Discussion

Regarding the ACO and Ant-Q results, the following conclusions can be drawn:

- Both algorithm seems to perform well, with quite good (or at least “decent” for the largest dataset) average displacements from the globally optimal solution.
- in general, both algorithms are pretty fast and well performing on small or medium datasets ($n \lesssim 100$), but the execution time becomes pretty important when approaching datasets with $n \gtrsim 100$ nodes. This behaviour is explained considering that Ant family algorithms are multiagent algorithm, and the best practice for an optimal tuning is known to require setting the number of ant agents $m \sim n$, thus the larger the dataset is the more internal iterations the algorithm will be doing.
- a comparison between the two algorithms can be done in terms of the percentage variation. Observing the plot in Fig. ?? it can be clearly stated that the Ant-Q has slightly better performances, especially in providing the best solution and typically having a better average execution time (even though the magnitude order remains similar between the two algorithms). Thus, the introduction of the Q-learning-like updating rule (Eq. 11) seems to improve the performance over the “simple” ACO. Therefore the hybrid approach performs better than the classic one. This results is in agreement with those of Gambardella and Dorigo in Ref. [7].
- it is worth to notice that one could increase the performances of such algorithms even in case of larger dataset, just providing more computational resources and time. The good news of this approach consist in being able to scale out pretty easily, just by setting up an MPI cluster⁶ and configuring an host-file for the parent-children scheduling. However, for our limited resources, the last runs on large datasets were pretty limited in the number of iterations, thus producing a wider gap with the globally optimal solution.

For as regards the evolutionary approach, GA and KGA in particular for this work, the following conclusions are drawn:

- Both algorithms perform well but, due to their nature, they require a large amount of iteration i.e. time, to reach good performance in terms of average displacements from the globally optimal solution.
- both algorithms are rather slow, especially if compared in terms of ratio between time and displacements from the optimal solution in average.
- comparing the two algorithms in terms of percentage variation is possible observing Fig. 3. GA seems to be more efficient on small dataset while KGA seems to suffer not in finding the optimal solutions for the sub-problems but in reconstruct the total optimal solution linking the sub-problems ones. This is due to the linking mechanism that could cause a small distortion for each linking operation causing its accumulation and amplification. Indeed bigger the dataset is, more efficient seems to become KGA compared with GA; where GA seems to substantially diverge from the optimal solution, KGA improve his performance as the problem dimension grows.
- it is worth to notice that both algorithms’ performance could be improved with a fine parameters tuning and providing more computational resources on a larger amount of time, maybe implementing a parallel computation approach.

Going further in comparison, it is worth to make a parallel between the performance of the Ant-family algorithms and the evolutionary ones:

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⁶For more info see <https://mpitutorial.com/tutorials/running-an-mpi-cluster-within-a-lan/>

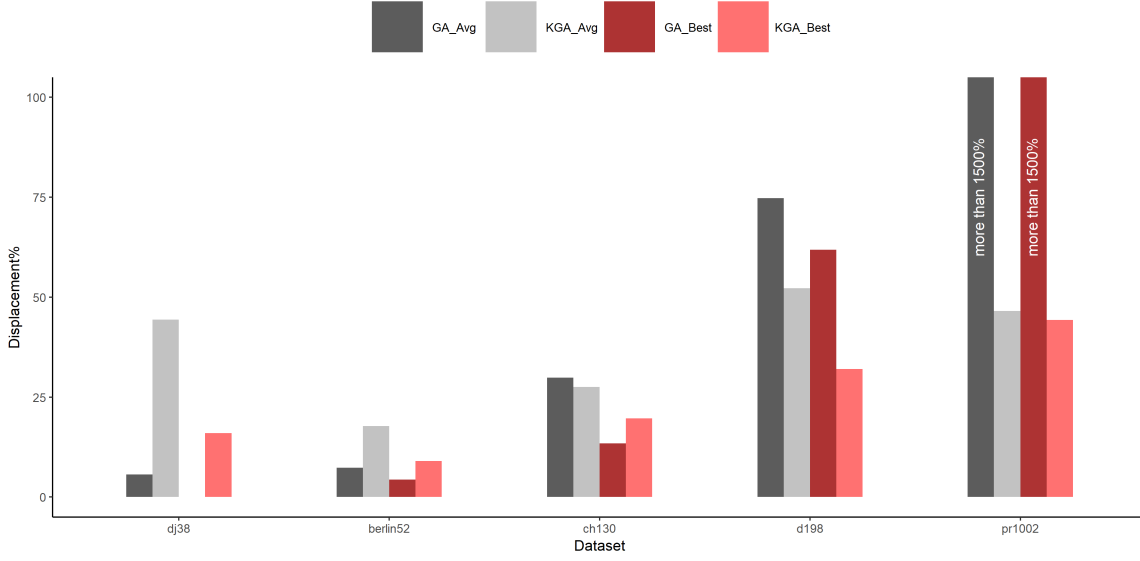


Figure 3: Percentage variation between AVG and Best GA and KGA algorithms' solutions for each dataset.

6 Conclusions

The main core objective of this work was to implement and test two interesting hybridized meta-heuristic approaches to the Travelling Salesman Problem.

The first approach presented in Sec. (1.1.1) and (1.1.2) consisted in developing the Ant Colony Optimization method, and integrating a reinforcement learning procedure into the basic structure of such algorithm, producing the so called Ant-Q algorithm.

The second part reported in Sec. (1.2.1) and (1.2.2) was based on the genetic algorithm, whose classic implementation was improved with the integration of a K-means algorithm and a custom method of obtaining the shortest path by sub-sequentially joining the clusters.

After executing some performance tests of several runs over the datasets presented in Sec. (2), the provided results demonstrate an effective improvement of the hybridized approach with respect to the classic version of each algorithm.

Furthermore, a comparison among the two types of methods can be done. The Ant family seems more likely to be applied on small or medium-sized problems, where it shows the best performances, whereas the evolutionary approach integrated with a clustering procedure is much more performant on large datasets, where it outperforms the classic Genetic implementation, with a reasonable cpu-time.

On large datasets both the family of algorithms do not obtain greatest results. The KGA utilization seems to be appropriate in order to have a “decent” sequence, that might be used for example as a starting point of another exploitation-based algorithm. The ACO and the Ant-Q becomes slow on higher dimensions running on four cpu-cores. However, further improvements in this direction could be obtained thanks to the parallel implementation, if a MPI cluster is provided. This would probably allow Ant-Q (in particular) to provide a good result even on large-scale problems.

Even further hybridization would be possible to implement, as a future scenario. For instance, it could be interesting to combine the ACO (or even better, the Ant-Q) and the KGA itself, leading to a method similar to that in ref. [20].

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