FEDERAL STATE AUTONOMOUS EDUCATIONAL INSTITUTION

OF HIGHER EDUCATION

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Report

on the practical task No. 4

“Algorithms for unconstrained nonlinear optimization. Stochastic and

metaheuristic algorithms”

Performed by

*Vdovkina Sophia*

*Syrchenko Arina*

*Academic group: J4133c*

Accepted by

Dr Petr Chunaev

St. Petersburg

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**Goal**

The use of stochastic and metaheuristic algorithms (Simulated Annealing, Differential Evolution, Particle Swarm Optimization) in the tasks of unconstrained nonlinear optimization and the experimental comparison of them with Nelder-Mead and Levenberg-Marquardt algorithms.

**Formulation of the problem**

1. Generate the noisy data , where , according to the rule:

where are values of a random variable with standard normal distribution. Approximate the data by the rational function

by means of least squares through the numerical minimization of the following function:

To solve the minimization problem, use Nelder-Mead algorithm, ﻿Levenberg-Marquardt algorithm and at least two of the methods among Simulated Annealing, Differential Evolution and Particle Swarm Optimization. If necessary, set the initial approximations and other parameters of the methods. Use as the precision; at most 1000 iterations are allowed. Visualize the data and the approximants obtained in a single plot. Analyze and compare the results obtained (in terms of number of iterations, precision, number of function evaluations, etc.).

1. Choose at least 15 cities in the world having land transport connections between them. Calculate the distance matrix for them and then apply the Simulated Annealing method to solve the corresponding Travelling Salesman Problem. Visualize the results at the first and the last iteration. If necessary, use the city dataset from https://people.sc.fsu.edu/~jburkardt/datasets/cities/cities.html

**Brief theoretical part**

Stochastic methods use randomization to help finding the optimum. Such that, randomness can help escape local optimum and increase the chances of finding a global optimum. Stochastic methods also do not guarantee an exact solution and convergence, but they can find a solution in a reasonable time.

Metaheuristic algorithms are a class of stochastic algorithms using a combination of randomization and local search. They are often inspired by nature or biological systems.

*Simulated annealing*

Simulated annealing is a probabilistic technique for approximating the global optimum of a given function, it was inspired by metallurgy, where it is a technique of controlled heating and cooling of a material. The internal processes of a metal are simulated by some mathematical system ad the goal is to bring the system, from an arbitrary initial state, to a state with the minimum possible energy. Temperature is used to control the degree of stochasticity during the randomized search. The temperature starts high, so that algorithm makes big steps around the search space until it finds the local minimum. Then the temperature slowly decreases, reducing the stochasticity and forcing the search to converge to a minimum. But before converging to some local minimum algorithm with some probability decides whether jump to another state or stay where it is. Simulated annealing is can used on functions with a lot of local minimums due to its ability to escape local minima.

*Differential evolution*

Differential evolution is a population-based metaheuristic search algorithm that optimizes a problem by iteratively improving a candidate solution based on an evolutionary process. It improves each individual in the population by combining it with other individuals and then it keeps the candidate solution with the best score or fits better for the particular problem. By having a large number of individuals distributed throughout the design space algorithm avoids becoming stuck in a local minimum.

*Particle swarm optimization*

Particle swarm optimization solves a problem by having a population of candidate solutions (dubbed particles) and moving these particles around in the search-space. Particle swarm optimization introduces momentum to accelerate convergence towards minimum. Each particle moves with respect to its local best-known position, but it also guided towards the best-known position in the search-space, that is updated while better positions are found by other particles. This is expected to move the swarm towards the best solutions.

**Results**

**Conclusion**

**Appendix**

Source code is available on