DOI: 10.34185/1991-7848.itmm.2023.01.015

APPLICATION OF MULTI-OBJECTIVE PARTICLE SWARM OPTIMIZATION FOR QUALITY CONTROL OF MECHANICAL PROPERTIES OF HIGH-STRENGTH STEELS

Togobytska Nataliya
University of Applied Sciences (HTW Berlin), *Treskowallee 8, 10318 Berlin, Germany*

Abstract. In many applications, it is common to have several objective functions have to be optimized simultaneously. Because of the multi-criteria nature of such optimization problems and sometimes competing objective functions, optimality of a solution has to be redefined relying on concept of Pareto optimality. A relatively recent heuristic technique called Multi-Objective Particle Swarm Optimization (MOPSO) has been found to perform very well in a wide range of multi-objective optimization problems. This paper explores the application of this technique for the optimization of mechanical properties of high-strength structural steels. MOPSO can be effectively applied for the solution of a bi-objective optimization problem to determine optimal chemical composition, achieving a trade-off between tensile strength and elongation-to-break for a big class of structural steels.

Keywords: multi-objective optimization, pareto front, structural steels, mechanical properties

Introduction. In contrast to the single-objective optimization case, multi-objective problems consist of several objectives that are necessary to be handled simultaneously. Mathematically, a multi-objective problem can be formulated as a vector of objectives $f_i(x), i = 1, \dots, k$ that must be optimized (min or max)

$$F(x) = \left(f_1(x), f_2(x), \dots, f_k(x)\right) \text{ such that } x \in R^n$$

$$\text{and } g_j(x) \le 0, \ j = 1, \dots m.$$

Then, we are interested in finding a solution, $x^* = (x_1, \dots, x_n)$, that minimizes/maximizes $F(x)$.

The multiple objectives $f_i(x)$ are often in conflict with each other, which makes the multi-objective problems more difficult to be solved than single-objective optimization problems. In these problems one tries to find the optimal trade-off solutions between different objectives, known as the search for the optimal *Pareto front* [1]. Any solution of Pareto optimal set is optimal in the sense that no improvement can be made on a component of the objective vector without worsening at least another of its components.

An analytical expression of the true optimal Pareto front is often difficult to obtain in a multi-objective optimization problem. Evolutionary algorithms like Genetic Algorithms and Particle Swarm Optimization are well suited to solving such kind of optimization problems, because they mimic natural processes that are inherently multiobjective [2]. In these heuristic algorithms one seeks to distribute the population of solutions in objective space as close as possible to the true optimal Pareto front.

Particle Swarm Optimization (PSO) is a swarm intelligence method that roughly models the social behavior of swarms. PSO uses an adaptable velocity vector for each particle, which shifts its position at each iteration of the algorithm (Fig.1). The particles are moving towards promising regions of the search space by exploiting information springing from their own experience during the search, as well as the experience of other particles [3]. There are a lot of *Multi-Objective Particle Swarm Optimization (MOPSO)* approaches and applications reported in the literature. The general MOPSO scheme can be described with the following pseudocode [3]:

```
Begin
        Initialize swarm, velocities and best positions
        Initialize external archive (initially empty)
        While (stopping criterion not satisfied) Do
For each particle
        Select a member of the external
 archive (if needed)
        Update velocity and position
        Evaluate new position
        Update best position and external
 archive
 End For
 End While
End
```

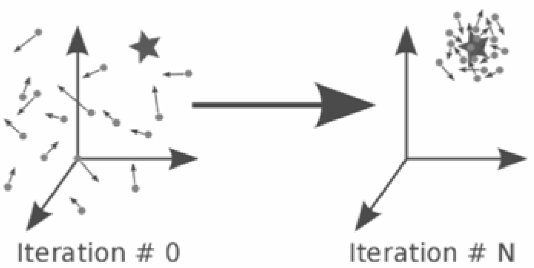

Figure 1 - Schematic representation of PSO. Source: https://esa.github.io/pagmo2/docs/cpp/algorithms/pso.html

Results and Discussion. In this paper, the MOPSO algorithm is used to optimize the mechanical properties of high-strength structural steels. The high strength level of structural steels gives potential for different industrial applications. The influence of alloying and microalloying on the mechanical properties of high-strength steels has been investigated in the previous papers [4, 5]. The regression models for tensile strength σ_B and elongation-to-break δ_5 , which incorporates the parameters of interatomic interaction Z^Y, d_{ml}, were derived based on an industrial data set [4]:

$$\sigma_B, MPa = 43757 + 1126 \cdot Z^Y - 31073 \cdot d_{ml} + 5407 \cdot d_{ml}^2$$

$$\delta_5, \% = -3554.54 + 48.26 \cdot Z^Y + 2434.84 \cdot d_{ml} - 420.24 \cdot d_{ml}^2.$$

A higher percent elongation usually indicates a better-quality material when combined with good tensile strength. Since there is generally an inverse relationship between the strength and the plastic properties of high-strength steels, an important task is to find a compromise setting of the parameters of interatomic interaction Z^Y, d_{ml}, that ensures the stabilization of the mechanical properties at the required level. This problem can be formulated as a multi-criteria optimization problem:

$\boldsymbol{max}(\sigma_B, \delta_5)$ under constraints $1.18 \leq Z^Y \leq 1.26,\ 2.75 \leq d_{ml} \leq 3.05$.

For the further calculations, the objectives σ_B, δ_5 are denoted by f_1, f_2 respectively. The MOPSO algorithm for this optimization problem was implemented based on the paper [6] and MATLAB Code [7]. The problem is solved using 200 particles, 100 iterations, archive size of 200, inertial weight of 0.4, c_1 =2, and c_2 =2. An approximation of the Pareto front and the initial distribution of particles is shown in Figure 2. The corresponding Pareto optimal solutions belong to the set $\{Z^Y, d_{ml} \mid Z^Y = 1.26,\ 2.897 \leq d_{ml} \leq 3.05\}$. In the next step, an optimal chemical composition can be obtained using an inverse transformation of calculated Pareto set with parameters of interatomic interaction [4]. Further research could be done on a combination of MOPSO with the desirability concept to incorporate expert knowledge and preference specification for mechanical properties of high-strength steels.

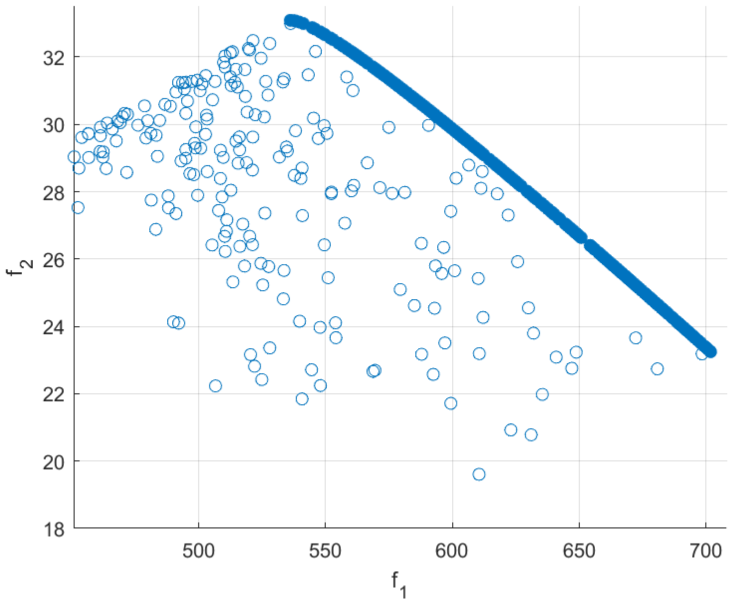

Figure 2 - Blue filled dots represent a Pareto front approximation, with objective functions f_1 and f_2 to be maximized. The points along the Pareto front are Pareto-optimal solutions in which f_1 objective cannot be improved without degrading at f_2 objective

References

1. Deb, K. (2001). Multi-Objective Optimization using Evolutionary Algorithms. John Wiley & Sons Ltd., West Sussex
2. Awad, M., Khanna, R. (2015). Multiobjective Optimization. In: Efficient Learning Machines. Apress, Berkeley, CA. https://doi.org/10.1007/978-1-4302-5990-9_10
3. Parsopoulos, Konstantinos E., and Michael N. Vrahatis. (2008). Multi-Objective Particles Swarm Optimization Approaches. Multi-Objective Optimization in Computational Intelligence: Theory and Practice, edited by Lam Thu Bui and Sameer Alam, IGI Global, pp. 20-42. https://doi.org/10.4018/978-1-59904-498-9.ch002
4. Babachenko, O., Kononenko, H., Snigura, I., & Togobytska, N. (2021), Optimisation of chemical composition of high-strength structural steels for achieving mechanical property requirements. Paper presented at ESAFORM 2021. 24th International Conference on Material Forming, Liège, Belgique. doi: 10.25518/esaform21.3654
5. Togobytska, N. (2022). Artificial neural network model for prediction of mechanical properties of steel. In International scientific and technical conference Information technologies in metallurgy and machine building, pp. 74-78
6. Coello, C. A. C., Pulido, G. T., Lechuga, M. S. (2004). Handling multiple objectives with particle swarm optimization. IEEE Transactions on evolutionary computation, 8(3), pp. 256-279.
7. Martínez-Cagigal V.(2023). Multi-Objective Particle Swarm Optimization (https://www.mathworks.com/matlabcentral/fileexchange/62074-multi-objective-particle-swarm-optimization-mopso), MATLAB Central File Exchange. Retrieved March 13, 2023.