Randomized Optimization: From Algorithmic Studies to Industrial Applications

Bogdan Filipič
Jožef Stefan Institute
Ljubljana, Slovenia
bogdan.filipic@ijs.si

ABSTRACT

As opposed to deterministic optimization techniques, randomized optimization algorithms rely on random choices when searching for good solutions to a given problem. They represent a viable alternative for solving real-world problems whose properties are usually unknown and their complexity too high to be solved with deterministic techniques. In our research group, we are specialized in studying and designing randomized optimization algorithms and deploying them in practice. In this paper we report on our algorithmic studies that have led to successful industrial applications. We illustrate these with two case studies from engineering design and production process optimization.

KEYWORDS

optimization, black-box problems, randomized algorithms, numerical simulation, visualization, engineering design, production

1 INTRODUCTION

Many problems in science, engineering and business can be formulated as optimization problems, where the task is to find the best solution among the possible alternatives with respect to a given criterion. Mathematics and, in particular, operation research provide various optimization methods that are applicable given that the problems meet certain preconditions, such as linearity, continuity, existence of derivatives, etc. Unfortunately, real-world problems rarely comply with these requirements. Frequently, their structure and properties are unknown, they may involve several possibly conflicting objectives as well as constraints. This makes them intractable for traditional mathematical optimization methods. However, with the rise of computing power, a new class of optimizers, called randomized or stochastic optimization algorithms [17] has emerged. Their key characteristic is that, unlike in deterministic mathematical methods, certain algorithm steps depend on random choices. Randomized algorithms search for good solutions according to some heuristic and handle the problems in a black-box manner, i.e., without dealing with their structure and properties. Many of them are population-based, as is the case, for example, with evolutionary algorithms [5].

In the Computational Intelligence Group of the Department of Intelligent Systems at the Jožef Stefan Institute, we have decades of experience in studying, designing and deploying randomized optimization algorithms. In this paper we report on our algorithmic studies that have led to successful industrial applications. The paper is further organized as follows. Section 2 outlines the research topics dealt with and the proposed algorithms. The next two sections present cases studies from their practical applications. Section 3 overviews our work in engineering design and focuses on the recent use case of designing an electric motor for the automotive industry. Section 4 lists the applications in production process optimization and presents a system developed to tune the parameters of a metallurgical production process. Section 5 summarizes our work and provides ideas for future development.

Information Society 2023, 9–13 October 2023, Ljubljana, Slovenia

2 ALGORITHMIC STUDIES

Our interest in randomized optimization was inspired by the introduction of genetic algorithms as a method to perform search, optimization, and machine learning [13]. After the initial experiments on test problems and first attempts at solving real-world problems, we specialized in evolutionary multiobjective optimization [2]. Our early achievement in this area was the design of the Differential Evolution for Multiobjective Optimization (DEMO) algorithm [16], which combines the search mechanism of single-objective Differential Evolution [18] with the concepts of multiobjective optimization from the NSGA-II algorithm [3] and finds multiple trade-off solutions in a single algorithm run.

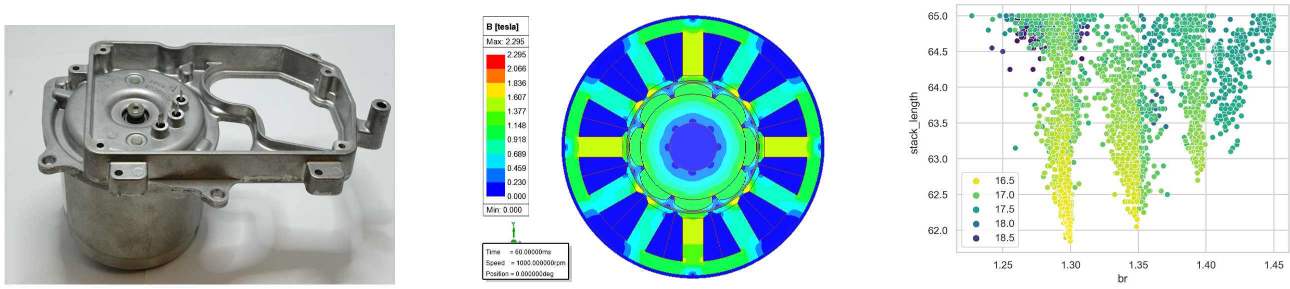
The algorithm was later extended to Asynchronous Master-Slave DEMO (AMS-DEMO) [4] suitable for solving computationally demanding problems, as it is parallelized and adjusted for both homogeneous and heterogeneous multiprocessor architectures. Another modification of the basic algorithm was DEMO based on Gaussian Process models (GP-DEMO) [15], which incorporates two practically relevant approaches: surrogate models for faster evaluation of solutions and newly defined relations for comparing solutions under uncertainty to minimize the effect of errors due to inaccurate surrogate model approximations.

Significant attention was also paid to the visualization of optimization results. This turned out to be useful in solving both artificial test problems and real-world problems as it helped better understand the problems themselves as well as the working of the algorithms. We introduced a method for visualizing fronts of nondominated solutions called visualization with prosections [19] and created a taxonomy of the existing visualization methods for multiobjective optimization [8].

3 ENGINEERING DESIGN OPTIMIZATION

We have approached several engineering design optimization problems using randomized algorithms. The addressed devices and the related optimization tasks were as follows:

- Electric motor for home appliances – determining the geometry of its rotor and stator such that the power losses are minimal [21];
- Energy supply system based on renewable sources – finding its configuration, i.e., the type and the number of its components (photovoltaic panels, batteries, etc.), such that both the proportion of unsupplied energy and the costs of the system construction and operation are minimal [6];



(a) (b) (c)

Figure 1: An electric motor for the automotive steering system: (a) a product example (source: MAHLE archive), (b) numerical simulation of the magnetic field (source: MAHLE archive), (c) visualization of candidate designs with respect to selected characteristics.

- Cyclone dust separator (a device for removing dust particles from gas streams, widely used in industry) – determining, through a number of design variables, its shape such that the device operates with maximum collection efficiency and minimum pressure drop [23].

A recent engineering design challenge we dealt with was the development of an electric motor for the automotive steering system [20] carried out for MAHLE Electric Drives Slovenija, an internationally recognized producer of components for the automotive industry. Specifically, a synchronous electric motor with surface-mounted magnets was considered. An example of the product is shown in Figure 1(a).

In the optimization problem formulation, both technical and economic aspects were involved. The task was to determine the geometry characteristics of the electric motor and the material properties of its components in such a way that the motor meets the technical requirements specified by the customer and its price is as low as possible. There are 13 design variables and seven constraints referring to the technical characteristics of the electric motor, given in the form of either minimum or maximum value to be respected. The optimization objective to be minimized is the total price of the electric motor, resulting predominantly from the costs of the magnets and the copper winding.

In design tasks of this kind, a numerical simulator capable of evaluating possible solutions (designs) is crucial for the automation of the design procedure. MAHLE uses the Ansys Maxwell simulator [1] based on the finite element method that, given the values of design variables, calculates the values of the regarded technical characteristics and the optimization objective (Figure 1(b) shows the result of the magnetic field simulation). This makes it possible to approach the problem in a black-box manner, where the designs are iteratively evaluated and improved. However, as numerical simulations are time-consuming, the key challenge is to set up the optimization process in such a way that it can find good solutions in acceptable time. To solve this design optimization problem, we implemented a prototype software environment incorporating measures to speed-up the optimization process, while additionally ensuring the robustness of solutions and supporting the design process with visualization.

The measures taken to speed-up the optimization process were the following:

- As an optimization algorithm, a specific version of the covariance matrix adaptation evolution strategy (CMA-ES) called lq-CMA-ES [14] was used, which partially replaces costly simulation-based solution evaluations with fast-calculating surrogate models.
- Solution evaluation was carried out through a custom-designed five-step procedure performing a sequence of solution checks and eliminating a large proportion of infeasible solutions without running the costly simulations.
- The most complex step of the solution evaluation procedure, the detailed numerical simulation, was parallelized to take advantage of the available multicore processors.

Robustness of electric motor designs is related to the limitations of manufacturing where the matching of products with the optimized design can only be ensured within certain tolerances. For this reason, the designs are required to be robust in that small changes in design variables, within the tolerances, do not significantly affect the characteristics of the electric motors. In the design process, this was checked by simulating a variety of designs slightly differing from the original one.

Finally, in addition to producing numerical results in the form of the optimized values of design variables and the related electric motor characteristics, the procedure was also required to provide insight into the solution space. For this purpose, the methods for data analysis and visualization were applied. Figure 1(c) shows an example of visualization where, for a chosen pair of design variables, the value of a selected electric motor characteristic is indicated by color.

The project resulted in a design of the considered electric motor model substantially outperforming the prototype initially developed by the company using a simpler optimization procedure. As the key achievement, the price of the product was reduced by 10% compared to the price of the initial version. Given that large series are manufactured, this represents substantial savings for the company and considerably improves their competitiveness in the market.

4 PRODUCTION PROCESS OPTIMIZATION

Our practically oriented studies and applied projects in production process optimization refer to the following processes and the related optimization tasks:

- Deep drawing (a particular kind of sheet metal forming used, for example, in the automotive industry for the manufacturing of car body parts) – increasing the process stability by tuning the input parameter values [12];
- Clothing production – finding an optimal sequence of steps in the processing of work orders to minimize the production preparation costs [11];

(a) (b) (c)

Figure 2: Continuous casting of steel: (a) pouring of molten steel into the mold where the casting process starts, (b) casting device (source: Štore Steel archive), (c) cooling of billets.

- Continuous casting of steel (a key process in steel production) – determining the values of process parameters such that the conflicting criteria for process safety, productivity, and product quality are fulfilled [9, 7].

Among these, the largest amount of our work was devoted to the optimization of steel casting. In this process, molten steel extracted from the furnace passes through a sequence of rolls and water sprays in the casting machine where it is cooled and shaped into semi-finished products. Of crucial importance for the quality of cast steel is the control of metal flow and heat extraction during casting. They depend on numerous process parameters, such as the casting speed and coolant flows. Finding the optimal values of process parameters is not trivial as the number of possible parameter settings grows exponentially with the number of parameters, and trial-and-error parameter tuning is unattainable in practice. Fortunately, numerical simulators of the process exist that, integrated with efficient optimizers, allow for automated computer-aided parameter tuning.

We were dealing with various problem formulations for several steel producers. Here we present an optimization system developed for and installed at Štore Steel, a steel company best known for their production of spring steels for the automotive industry. A new casting device at the plant was considered and the quality of cast steel was of primary concern. Figure 2 shows the initial stage of the continuous casting process, the casting device, and the outcome, i.e, cast steel in the form of billets.

The optimization problem was formulated to include six input variables (process parameters) subject to boundary constraints and three output variables indicating the process suitability and, consequently, the expected steel quality. For output variables, boundary constraints and target values were specified in advance. The goal of optimization was to find the values of process parameters such that the resulting values of output variables respect the boundary constraints and their deviations from the respective target values are as small as possible.

Starting with this problem formulation, we designed and implemented a software system to automate the process parameter tuning [10]. The system consists of the following components:

- An optimization algorithm to search the space of parameter settings and identify the settings representing trade-offs between the objectives;
- An interface to the numerical simulator of the continuous casting process to evaluate the parameter settings encountered by the optimization algorithm;
- A visualization method to present the optimization results and support their analysis.

The optimization algorithm used is Differential Evolution for Multiobjective Optimization (DEMO) [16]. While exploring the process parameter space using population-based search, it invokes the simulator to assess the quality of candidate parameter settings. Progressively, it converges to a set of trade-of solutions.

As a simulator, a numerical model of the steel casting process based on a meshless method [22] is deployed, designed and calibrated for the considered casting machine during its introduction into production. Given the values of input variables, the simulator numerically evaluates the casting process and returns the values of output variables.

Visualization of solutions (process parameter settings) resulting from the optimization procedure is done in parallel coordinates. This is a method suitable for visualizing multidimensional spaces. Each dimension corresponds to a parallel axis and a solution is represented as a polyline through the related vertices on the axes. As illustrated in Figure 3, both input and output values of solutions are shown in a single plot. Moreover, the user can interactively analyze the solutions depending on the requirements for a particular product order. By indicating the intervals for selected variables (as shown in the figure for the first two output variables), one can see what input values are required and how they affect the remaining output values.

The practical importance of this optimization system is in that it automates the process parameter optimization and in this way replaces the time consuming trial-and-error experiments carried out previously when only the numerical simulator was available. The automation is particularly beneficial as parameter tuning has to be performed individually for each steel grade. As a result, the company is more flexible in responding to customer requests and achieves a higher quality of their products.

5 CONCLUSION

Randomized optimization is the primary research topic of our research group. We have contributed to the field with new algorithms exhibiting competitive performance on multiobjective optimization problems, as well as with the methodological insights into visualization of solutions for this type of problems.

Potential industrial users often see the fact that randomized optimization algorithms generally return suboptimal solutions and produce different results over repeated runs as their critical disadvantage. However, for problems not amenable to mathematical treatment these algorithms may be the only viable approach. As frequently found in practice and confirmed by our case studies as well, substantial gains may result from their deployment.

Our further research efforts are directed towards shifting from black-box to gray-box problem handling, where the idea is to

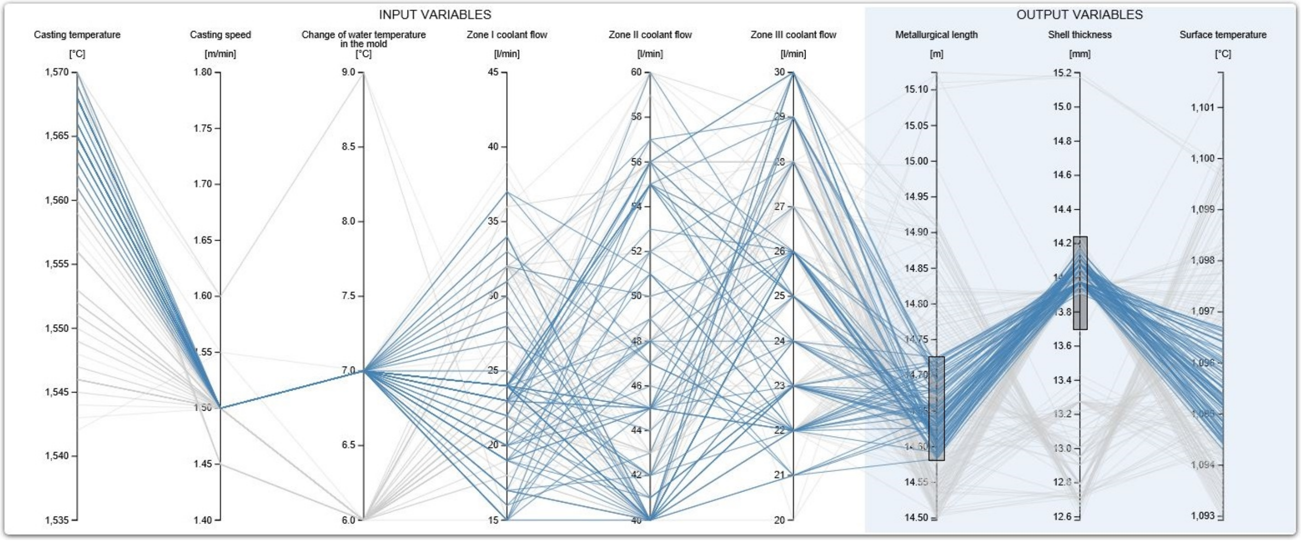


Figure 3: Visualization of optimized process parameter settings in parallel coordinates (blue color indicates solutions selected by the user).

characterize the problems with features extracted from the samples of their solutions and then use these features to better understand the problems [24]. As a future step, problem features will be matched with algorithm performance to help select the most efficient algorithm for a given problem. Moreover, in the applied work we plan to expand from solving specific problems to providing optimization environments capable of solving sets of related problems and offering more flexibility to the users.

ACKNOWLEDGEMENTS

We acknowledge the financial support from the Slovenian Research and Innovation Agency (research core funding No. P2-0209 and project No. N2-0254) and the funding from our industry partners Štore Steel d.o.o. and MAHLE Electric Drives Slovenija d.o.o. We also acknowledge the support from the Office for Substantive Project Support, Technology Transfer and Innovation and the Office for Industrial Liaison at the Jožef Stefan Institute in forming the partnerships and managing intellectual property rights.

REFERENCES

[1] Ansys, Inc. 2023. Ansys Maxwell, Low frequency EM field simulation. Retrieved 16 August 2023 from https://www.ansys.com/products/electronics/ansys-maxwell.

[2] Kalyanmoy Deb. 2001. *Multi-Objective Optimization Using Evolutionary Algorithms*. John Wiley & Sons, Chichester, UK.

[3] Kalyanmoy Deb, Amrit Pratap, Sameer Agarwal, and T. Meyarivan. 2002. A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE Transactions on Evolutionary Computation*, 6, 2, 182–197. DOI: 10.1109/4235.996017.

[4] Matjaž Depolli, Roman Trobec, and Bogdan Filipič. 2013. Asynchronous master-slave parallelization of differential evolution for multiobjective optimization. *Evolutionary Computation*, 21, 2, 261–291. DOI: 10.1162/EVCO_a_00076.

[5] Agoston E. Eiben and James E. Smith. 2015. *Introduction to Evolutionary Computing*. (2nd ed.). Springer. DOI: 10.1007/978-3-662-44874-8.

[6] Bogdan Filipič and Ivan Lorencin. 2012. Evolutionary multiobjective design of an alternative energy supply system. In *2012 IEEE Congress on Evolutionary Computation (CEC)*. IEEE, 395–400. DOI: 10.1109/CEC.2012.6256159.

[7] Bogdan Filipič, Miha Mlakar, and Tea Tušar. 2015. Multiobjective optimization of process parameters in steel production. In *Proceedings of the 13th International Symposium on Operational Research in Slovenia, SOR '15*. Slovenian Society Informatika, Section for Operational Research, 99–104.

[8] Bogdan Filipič and Tea Tušar. 2018. A taxonomy of methods for visualizing Pareto front approximations. In *Proceedings of the Genetic and Evolutionary Computation Conference, GECCO '18*. ACM, 649–656. DOI: 10.1145/3205455.3205607.

[9] Bogdan Filipič, Tea Tušar, and Erkki Laitinen. 2007. Preliminary numerical experiments in multiobjective optimization of a metallurgical production process. *Informatica*, 31, 2, 233–240.

[10] Bogdan Filipič, Jernej Zupančič, and Tea Tušar. 2018. KN3-Opt: Optimization of steel continuous casting on the KN3 caster. Software. Version 1.2. Ljubljana: Jožef Stefan Institute, (2018).

[11] Iztok Fister, Marjan Mernik, and Bogdan Filipič. 2010. A hybrid self-adaptive evolutionary algorithm for marker optimization in the clothing industry. *Applied Soft Computing*, 10, 2, 409–422. DOI: 10.1016/j.asoc.2009.08.001.

[12] Gašper Gantar, Karl Kuzman, and Bogdan Filipič. 2005. Increasing the stability of the deep drawing process by simulation-based optimization. *Journal of Materials Processing Technology*, 164-165, 1343–1350. DOI: 10.1016/j.jmatprotec.2005.02.099.

[13] David E. Goldberg. 1989. *Genetic Algorithms in Search, Optimization and Machine Learning*. Addison-Wesley Longman Publishing, Boston, MA, US.

[14] Nikolaus Hansen. 2019. A global surrogate assisted CMA-ES. In *Proceedings of the Genetic and Evolutionary Computation Conference, GECCO '19*. ACM, 664–672. DOI: 10.1145/3321707.3321842.

[15] Miha Mlakar, Dejan Petelin, Tea Tušar, and Bogdan Filipič. 2015. GP-DEMO: Differential evolution for multiobjective optimization based on Gaussian process models. *European Journal of Operational Research*, 243, 2, 347–361. DOI: 10.1016/j.ejor.2014.04.011.

[16] Tea Robič and Bogdan Filipič. 2005. DEMO: Differential evolution for multiobjective optimization. In *Evolutionary Multi-Criterion Optimization, EMO 2005* (Lecture Notes in Computer Science). Vol. 3410. Springer, 520–533. DOI: 10.1007/978-3-540-31880-4_36.

[17] Johannes Josef Schneider and Scott Kirkpatrick. 2006. *Stochastic Optimization*. Springer. DOI: 10.1007/978-3-540-34560-2.

[18] Rainer Storn and Kenneth Price. 1997. Differential evolution – A simple and efficient heuristic for global optimization over continuous spaces. *Journal of Global Optimization*, 11, 4, 341–359. DOI: 10.1023/A:1008202821328.

[19] Tea Tušar and Bogdan Filipič. 2015. Visualization of Pareto front approximations in evolutionary multiobjective optimization: A critical review and the prosection method. *IEEE Transactions on Evolutionary Computation*, 19, 2, 225–245. DOI: 10.1109/TEVC.2014.2313407.

[20] Tea Tušar, Peter Korošec, Jordan Cork, Bogdan Filipič, Matija Cej, Boštjan Drnovšek, and Jurij Strgulec. 2023. Simulation-based optimization of cogging torque in electric motor design – Phase 3: Solving the asymmetric problem. Technical report IJS-DP 14344. Jožef Stefan Institute, Ljubljana.

[21] Tea Tušar, Peter Korošec, Gregor Papa, Bogdan Filipič, and Jurij Šilc. 2007. A comparative study of stochastic optimization methods in electric motor design. *Applied Intelligence*, 27, 2, 101–111. DOI: 10.1007/s10489-006-0022-2.

[22] Robert Vertnik and Božidar Šarler. 2009. Simulation of continuous casting of steel by a meshless technique. *International Journal of Cast Metals Research*, 22, 1-4, 311–313. DOI: 10.1179/136404609X368064.

[23] Aljoša Vodopija, Beate Breiderhoff, Boris Naujoks, and Bogdan Filipič. 2021. Design of cyclone dust separators: A constrained multiobjective optimization perspective. In *2021 IEEE Congress on Evolutionary Computation (CEC)*. IEEE, 1983–1990. DOI: 10.1109/CEC45853.2021.9504991.

[24] Aljoša Vodopija, Tea Tušar, and Bogdan Filipič. 2022. Characterization of constrained continuous multiobjective optimization problems: A feature space perspective. *Information Sciences*, 607, 244–262. DOI: 10.1016/j.ins.2022.05.106.