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# **Introductory Chapter: Nature-Inspired Methods for Stochastic, Robust, and Dynamic Optimization**

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Additional information is available at the end of the chapter

<http://dx.doi.org/10.5772/intechopen.78009>

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## **1. Introduction**

Optimization is one of the most studied fields in the wide field of artificial intelligence. Hundreds of studies published year after year focus on solving many diverse problems of this kind by resorting to a vast spectrum of solvers. Within this class of problems, several problem flavors can be identified depending on the characteristics of their constituent fitness functions and support of their optimization variables, such as linear, continuous or combinatorial. Efficiently tackling such optimization problems requires huge computational resources, especially when the formulated problem at hand represents complex real-world situations with hundreds of variables and constraints. For these reasons and due to the inherently practical utility of optimization algorithms, very heterogeneous problem-solving approaches have been developed by the community over the last decades for their application to these problems. From a general perspective, optimization methods can be classified as exact, heuristics, and metaheuristics. In this chapter, the focus is placed on the latter two families, in particular in those algorithmic variants where biological processes observed in nature have lied at the motivating core of the operators underlying their search mechanisms. In other words, we will center our attention on Nature-Inspired methods for efficient optimization and problem solving.

In this context, Nature-Inspired algorithms have recently gained ever-growing popularity in the community, with an unprecedented body of the literature related to assorted algorithmic approaches suited to deal with problem formulations by leveraging the self-learning capability of their mimicked natural phenomena. The rationale behind the momentum acquired by this broad family of methods lies in their outstanding performance, which has hitherto been evinced in hundreds of research fields and problem scenarios. In this regard, many different inspirational sources have been proposed for constructing optimization methods, such as the behavioral patterns of bats [1], fireflies [1], bees [2] or the stigmergy by which ants communicate to each

other when looking over an area for a food source [3], which add to the mechanisms behind genetic inheritance that stimulated the advent of the seminal branch of genetic algorithms [4].

In recent years, most of these Nature-Inspired methods have been successfully applied to a wide variety of topics. To cite a few, the aforementioned Bat algorithm has been applied to problems related to energy [5], sports training planning [6] or logistics [7, 8], whereas the Firefly Algorithm has been applied to selected applications in medicine [9], job-shop scheduling [10] or goods distribution, and logistics [11, 12]. This is a very reduced yet exemplary bibliographic sample of the heterogeneous research activity around Nature-Inspired methods. A thorough review of the state of the art in this topic can be extensive, reason for which many comprehensive surveys have been lately contributed to reflect the huge literature produced around certain algorithms. Nevertheless, Genetic Algorithms and Ant Colony Systems are, arguably, the most widely resorted algorithms of this kind, with recent literature compendiums focused on these both approaches appearing in the literature on a yearly basis [13, 14].

This introductory chapter contributes to this line of research by presenting applications of Nature-Inspired solvers to three specific branches of optimization problems, namely, stochastic, dynamic, and robust optimization. We next provide a more elaborated presentation of each of such branches.

## 2. Dynamic optimization

In optimization problems, it is often the case that the parameters based on which fitness function(s) and constraints are defined remain unaltered over the period of time in which the solution obtained by the solver is considered to be optimal. Therefore, such parameters are assumed to be known a priori and fixed from the very beginning of the problem solving process. In dynamic optimization, however, this stability condition may not hold, this one or more constraints and/or fitness function of the problem can vary dynamically along time, even after the problem is solved and the solution is applied. The setup can be even more involved if new parameters appear at any step of the process, which must not only be included in the problem formulation but also accommodated by the technique at hand. Due to these exceptional situations, this casuistry demands efficient algorithmic means to solve optimization problems in an on-line fashion.

Dynamism in any aspect of the problem is a practical circumstance that emerges in almost any field where the context of the problem evolves along time due to exogenous factors to the initially formulated problem statement. One of the scenarios, where dynamic optimization is under active investigation, is transportation and mobility, in which the dynamism of the considered parameters can force re-planning previously traced routes, even if the vehicle is already on the road. This hypothesized case can be produced either by the appearance of any incident over the road network or the arrival of unexpected information that was not present when the initial route optimization was performed. An example of this kind of problem was presented in [15], in which a vehicle routing problem is modeled by integrating the information about future

customers' dynamic requests. Another problem prone to considering this characteristic is the job-shop scheduling problem and its multiple variants, as can be seen in recently published studies such as [16, 17]. Several interesting surveys are available on this topic, such as [18], in which the application of swarm intelligence methods to dynamic optimization is reviewed. In [19], on the other hand, Evolutionary Algorithms are analyzed for the same class of optimization problems.

### 3. Stochastic optimization

Stochastic optimization is another problem variant that finds its motivation in real application scenarios. This class of optimization problems can be defined as the process of maximizing or minimizing the value of a mathematical or statistical function, in which one or more of its values are subject to randomness. This stochastic nature may involve random objective functions and/or random restrictions, which ease the modeling of real-world problems subject to non-negligible sources of uncertainty, imprecision or randomness.

The need for stochastic optimization techniques emerge from a wide variety of real-world problems related to business analytics, electrical power production or energy management, among many others. In [20], for example, the so-called unit commitment problem is endowed with this feature to model and handle the uncertainty of the electric power generation process in the scheduling and dispatching of the produced energy. On the other hand, the authors in [21] regard power system management as a stochastic optimization problem, considering microgrids capable of controlling their local generation and demand with the presence of an uncertain amount of generated renewable energy.

Focused on Nature-Inspired techniques, examples such as the one found in [22] are worth to be mentioned. In this work, a Firefly Algorithm is used to tackle a multi-objective active/reactive power dispatch problem, with the existence of wind generation and load uncertainties. Another example can be accessed in [23], in which a Genetic Algorithm is utilized for efficiently solving a condition-based maintenance optimization problem subject to uncertainties.

### 4. Robust optimization

The third class of optimization problems targeted by this chapter is robust optimization, which denotes a branch of problems where one or more variables that compose the problem is also subject to uncertainty. In this case, however, the scope is placed on the robustness of the produced solutions against the variability of the constraints affected by uncertainty (e.g., the target is always placed on fulfilling simultaneously all constraints disregarding the statistical variability of the problem), as opposed to stochastic optimization which aim at satisfying the constraints up to a prescribed level of probability. This being said, different types of robust optimization problems can be modeled depending on how extreme values for the variable

parameters are formulated. One of these types is referred to as local robustness [24], where a measure of robustness is designed to accommodate small perturbations with respect to the nominal value of the parameter that undergoes stochastic variability. On the other hand, probabilistically robust optimization models [25] quantify the uncertainty in the real value of the parameter of interest using a probability distribution function. Additional classifications are global robustness [24], or non-probabilistic robust optimization models [26].

As has been pointed along this introduction, uncertainty is present in lots of real-world situations. For this reason, robust optimization has also been frequently used for modeling a wide variety of real problems, belonging to different knowledge areas, such as supply chain network design [27] or food distribution [28].

## 5. Conclusions

This introductory chapter highlights the potential that Nature-Inspired solvers may bring to stochastic, robust, and dynamic optimization problems. Nature has learned from itself from the very beginning of Earth, with manifold processes and intelligent behaviors that have naturally evolved over ages to attain high levels of adaptability and efficiency. It is now time for researchers, lecturers, and practitioners interested in Nature-Inspired optimization to shift their target and span the application of this algorithmic branch to these optimization problems, far less studied so far by the community than other formulated optimization problems.

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