



HOW TO DESIGN  
**OPTIMIZATION ALGORITHMS**  
BY APPLYING NATURAL BEHAVIORAL  
PATTERNS

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**Bentham Books**

# **How to Design Optimization Algorithms by Applying Natural Behavioral Patterns**

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# **How to Design Optimization Algorithms by Applying Natural Behavioral Patterns**

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ISBN (Online): 978-981-14-5959-7

ISBN (Print): 978-981-14-5957-3

Paper Back (Online): 978-981-14-5958-0

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## FOREWORD

Collective intelligence means that instead of using one thought, one can use multiple sets of thoughts, and collective intelligence in nature has greatly helped its survival. The meta-heuristic algorithms make use of all sources and provide a structure based on natural phenomena. Hence, the source that the algorithms use can determine their type and determine their quality. While there are some algorithms that are not suitable, most of the algorithms that used the natural resource were able to create a suitable framework under an optimization algorithm.

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## **PREFACE**

Most of the books presented by respected researchers in the field of optimization have introduced algorithms. So I thought young researchers and students needed a reference to research in this area and create their own algorithm. Nature has always been full of secrets in the history of mankind, and from time to time, human beings discover some of these mysteries. But there is still much to be desired until the day that man reaches the secrets of nature. With these discoveries, he has been able to propose important mechanisms based on these mysteries of nature. In this book, I talk mostly to young people and students who are interested in science. I try to share with them the little science I have in this area.

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## **DEDICATION**



I dedicate this book to the soul of Ms. Narjes Khanalizadeh. She was the first Iranian nurse to die of coronavirus. Narjes was born in 1995 in the city of Rudsar in northern Iran. After graduation, she worked as a nurse at the emergency department of Lahijan city. Narjes Khanalizadeh, on February 23, 2020, after the widespread outbreak of coronavirus in Iran, with similar complications of the coronavirus, lost consciousness and fell to the ground while taking care of patients at work. Narjes Khanalizadeh died in the afternoon of February 25, 2020 at Milad Hospital in Lahijan.

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## **Introduction to Optimization**

**Abstract:** Finding the best answer among the various solutions to complex and mathematical problems is called optimization. There are two types of optimization problems; continuous optimization and discrete optimization. Finding the solution in these environments is the best solution for that particular solution. Optimization exists in many fields and sciences, and it shows that if researchers provide the most quality optimization algorithms, it can have a great impact on human life. Optimization is similar to finding a treasure in an area. In this analogy, you have to mobilize a crowd to find this treasure. Since the population does not know the location of the treasure from the beginning, these populations will start searching at random and will reach near to it at a certain time. The topic of the search here is very important. It is very important to find a mechanism that can best organize the population. The search engine must follow certain ideas and rules. In the optimization problem, the most important step is proper search. In optimization issues, the concept of the best answer, best search, best solution and best organization is desired. Nowadays, optimization can be applied everywhere we deal with big data.

**Keywords:** Algorithm, Environments, Mathematics, Nature, Optimization, Space.

Optimization problems are called complex and mathematical problems that are more complex than other problems. There are two types of continuous and discrete variables in optimization problems. In a discrete optimization problem, we are looking for an object such as an integer, permutation or graph from a countable set. Problems with continuous variables include constrained problems and multimodal problems. It can be said that optimization is a kind of mathematical programming. As such, optimization has been able to solve many problems in the sciences, including physics, biology, engineering, economics and business. In most cases there is some kind of mathematical problem that needs to be solved. Algorithms convert and solve these problems into mathematical problems.

The historic term mathematical programming, broadly synonymous with optimization, was coined in the 1940s before programming became equated with computer programming. Mathematical programming includes the study of the mathematical structure of optimization problems, the invention of methods for

solving these problems, the study of the mathematical properties of these methods, and the implementation of these methods on computers. Faster computers have greatly expanded the size and complexity of optimization problems that can be solved. The development of optimization techniques has paralleled advances not only in computer science but also in operations research, numerical analysis, game theory, mathematical economics, control theory, and combinatory.

Optimization must have to consider three main problems. The first problem is that the answer is not exactly clear what. Whether the answer is a minimum number or a range of company costs, this type of answer must be precisely specified. The second problem is that sometimes it is necessary to manipulate values rather than an answer. Examples include quantities of stock to buy or sell the amount of different resources that must be allocated to different production activities, the route followed by the vehicle through the traffic network, or the policies that must be supported by a candidate. The final problem with optimization is that the answer area or the space of the item must be specified. For example, a production process may not require more resources than the available resources and it may not use less than zero resources. In this broad framework, optimization problems can have different mathematical properties. Mathematical optimization or mathematical programming is the selection of a best element (with regard to some criterion) from some set of available alternatives [1]. Optimization problems from computer science and engineering to operations research and economics, and the development of solution methods has been of interest in mathematics [2].

In the simplest case, an optimization problem consists of maximizing or minimizing a real function by systematically choosing input values from within an allowed set and computing the value of the function. The generalization of optimization theory and techniques to other formulations constitutes a large area of applied mathematics. More generally, optimization includes finding “best available” values of some objective function given a defined domain (or input), including a variety of different types of objective functions and different types of domains.

During the optimization, the initial algorithms are studied by the different methods and the obtained information is used to improve a thought or method. An optimization is a mathematical tool, which is concerns with finding the answers to many questions about the quality of solutions of different problems. The term of “the best” implicitly suggests that there are more than one solution to a given problem, which of course the solutions don’t have the identical values. The definition of the best solution depends on the discussed problem as well as the allowable error value. So, the way that the problem is formulated in which, also

has a direct impact on the quality of the best solution. Some problems have a clear response; such as the best player of a sport branch, the longest day of the year and solution of an ordinary first grade differential equation are examples that can be named as easy problems. In contrast, some problems have the various maximum or minimum solutions known as the optimal or extreme points and probably would be the best answer to a relative concept. The best work of art, the most beautiful landscape and the most dulcet track of music are among examples that can be said for these problems. Optimization is changing the inputs and characteristics of a device, a mathematical process or an experimental test in a way that the best output or result achieved. Inputs are the variables of a process that are referred to as the objective function, the cost function, or the fitness function.

Optimization is a process followed to improve something. A thought, idea or plan raised by a scientist or an engineer may get better through optimization procedure. During optimization, the initial conditions are investigated through different methods, and the obtained information is used to improve a thought or the used methods. Optimization is a mathematical tool used to find answers of many questions on how various solutions to problems are used. Optimization deals with finding the best response to a problem. The word “best” implies that there is more than one response to a problem but they are of different values. The definition of the “best” response depends on the problem, the solution and the amount of the permissible error. Therefore, the formulation also affects the definition of the best answer directly. Some problems have certain responses; the best player in a sport, the longest day of the year and the answer to an ordinary differential equation of first grade are some examples of simple problems. In contrast, some problems have several maximum or minimum answers known as optimal points or Extremum, and are probably the best answer to a relative concept. The best work of art, the most beautiful landscapes and the most pleasant piece of music can be named as examples of such problems, and Swarm Intelligence is a type of artificial intelligence technique established on the basis of collective behavior in decentralized and self-organized systems. These systems have populations that are purposefully and socially connected to one another and generate search. Usually these populations are automatically connected to each other and do not require special management. This kind of self-adaptive movement of populations makes the implementation mechanism in different systems easier.

Optimization refers to changing the input and characteristics of a device, or a mathematical process or an empirical test so that the best output or result would be achieved. The inputs are the variables of the process or function, namely objective function, cost function or fitness function. The output is defined as cost, benefit or fitness. In this book, according to many articles related to the topic, all

## Nature and Optimization Algorithms

**Abstract:** New algorithms have been developed to see if they can cope with these challenging optimization problems. Among these new algorithms, many algorithms, such as particle swarm optimization, cuckoo search, and firefly algorithm, have gained popularity due to their high efficiency. In the current literature, there are about 40 different algorithms. It is a challenging task to classify these algorithms systematically. In this chapter, the reader becomes familiar with the source of nature so that he can come up with an idea. Therefore, the first step in building and delivering a nature-inspired algorithm is to become familiar with nature and understand its features. Nature is a great source of inspiration for all stages of human life. In nature, creatures and structures always find solutions to their problems. Hence, it is nature that plays the leading role. Nature-inspired optimization algorithms are always some of the best mechanisms to solve complex problems. In this chapter, the reader will be introduced to a variety of nature-based optimization algorithms. Optimization algorithms are introduced and their techniques will be examined. This chapter has a history of nature-inspired algorithms whose evolution is visible. Researchers have tried to draw inspiration from natural resources as well as animals from nature that provided algorithms that have helped researchers in many problems. This chapter can also introduce readers to the history of making nature-based algorithms.

**Keywords:** Algorithm, Cost, Meta-heuristic, Nature, Optimization, Problem.

Nature-inspired algorithms all use a unique order in nature. These ideas have all come from field research and laboratory research on natural animals and natural phenomena. It is best to look around for ideas in nature and find the greatest effectiveness from the smallest of behaviors. How an ant moves with grain, how it carries it, and how it moves. How a bird learns to fly from a bird near it, how lions hunt in the jungle. We can even think of phenomena. How the clouds fertilize, and how it rains, and even how different generations of mankind have evolved with each other throughout history, reaching modern life. Studies have been conducted in recent years that have proposed different optimization algorithms based on different shapes of nature. Table 1 is a description of these efforts [8].

**Table 1.** Various swarm based optimization algorithms.

<b>AF Algorithm</b> <i>Cheng et al.</i>	<b>2018</b>
<b>whale optimization algorithm</b> <i>S Mirjalili, A Lewis</i>	<b>2016</b>
<b>SSPCO Algorithm</b> <i>Omidvar et al.</i>	<b>2015</b>
<b>Wolf search</b> <i>Tang et al.</i>	<b>2012</b>
<b>Bat Algorithm</b> <i>Yang</i>	<b>2010</b>
<b>Eagle Strategy</b> <i>Yang and Deb</i>	
<b>Firefly Algorithm</b> <i>Yang</i>	
<b>Cuckoo Search</b> <i>Yang and Deb</i>	<b>2009</b>
<b>Artificial Bee Colony</b> <i>Karaboga and Basturk</i>	<b>2007</b>
<b>Monkey Search</b> <i>Mucherino and Seref</i>	
<b>Cat Swarm</b> <i>Chu et al.</i>	<b>2006</b>
<b>Bees Algorithm</b> <i>Pham et al.</i>	
<b>Bacterial Foraging</b> <i>Passino</i>	<b>2002</b>
<b>Fish Swarm</b> <i>Li et al.</i>	
<b>Particle Swarm Algorithm</b> <i>Kennedy and Eberhart</i>	<b>1995</b>
<b>Ant Colony Optimization</b> <i>Dorigo</i>	<b>1992</b>

Genetic algorithm is one of the most popular algorithms of the new generation and is probably one of the first evolutionary algorithms in the field of optimization. A person named John Holland and his colleagues were able to draw inspiration from the genetic evolutionary system of natural organisms and develop a genetic algorithm. This algorithm is very effective in solving problems dealing with discrete numbers [9].

Genetic algorithm is one of the algorithms inspired by the natural structure and very successful. This algorithm has become one of the best optimization algorithms because it has been able to solve many difficult problems. The initial population of this algorithm is called the chromosome. Each chromosome consists of several females. Each chromosome is then subjected to cost function and its cost is determined. The most elusive chromosomes are put into the mating phase, which consists of two main cross-sections and mutations, resulting in a new and better population using this mating. Genetic algorithm is a conception of the generation evolution of living beings that could create an applied role in many scientific fields. Evolution Strategy was an evolutionary algorithm that used the natural evolutionary process to solve its problems. This algorithm was also introduced by Rechenberg in the early 1960s [10, 11].

Another optimization algorithm this decade called Evolutionary Programming (EP) by L.J. Foggel was introduced, inspired by the evolution in the field of artificial intelligence [12]. After the personal genetic algorithm called Kosa introduced a similar algorithm called the Genetic Programming (GP) algorithm in 1990 which was an interesting way of looking for the optimal solution. This algorithm almost automatically provided a solution to the problem [68]. This algorithm created a computer program from the process of solving an optimization problem and introduced it as the optimal solution [13].

Differential Evolution Algorithm (DE) is one of the most popular algorithms in the world of optimization algorithms [14]. This algorithm was proposed by Storn and Price to solve polynomial problems and its results showed that it is an acceptable algorithm for solving optimization problems.

The particle swarm optimization algorithm was introduced in 1995 by James Kennedy and Russell Eberhart, who was inspired by the crowd of birds in flight [15].

The algorithm is inspired by the behavior of birds when searching for food. The bird algorithm has a simple mechanism for implementation and simulation and is used in many engineering sciences and so on. In this algorithm, the population is randomly initialized and then the cost of each population is determined. The best local population and the best general population are identified. Each population moves in space according to the equation of velocity and motion, and at the end the final answer is determined [16 - 18]. This algorithm solves the problem of the back gypsy best known as the SF.

Particle swarm optimization algorithms and genetic algorithms combined to solve many difficult problems [19].

## How to Formulate Natural Ideas in Several Algorithms

**Abstract:** This chapter introduces examples of nature-inspired algorithms presented by authors in recent years. These algorithms all use the source of nature, and the nature and behavior of some animals are the main basis of these algorithms. These algorithms show the orderly behavior of some natural animals and show how this targeted order becomes an algorithm. Understanding these algorithms can help the reader understand how to transform the idea of nature into meaningful equations. We present some examples of these algorithms in this chapter to familiarize the reader with the order in some natural animals. Also, in this chapter, we can understand how to transform this natural order into meaningful equations. These meaningful equations are introduced in the form of an optimization algorithm. In this chapter, the algorithm SSPCO that inspired by the behavior of See-see partridge chickens, SSPCO algorithm based on chaotic population, data clustering using algorithm SSPCO algorithm, data clustering with algorithm chaotic SSPCO, Solving the Travelling salesman problem with the help of SSPCO algorithm, escape from hunter particle swarm optimization algorithm and birds algorithm based on classical condition learning, provided. In this chapter, we are going to introduce the reader to a number of algorithms presented and published by the author of the book. We are going to understand how an idea becomes a mathematical formula. Articles are available in the magazines which can be referred to for additional details.

**Keywords:** Algorithm, Equations, Nature-inspired, Optimization, Order.

### 3.1. SSPCO ALGORITHM (SEE-SEE PARTRIDGE)

The basic idea of this optimization algorithm is taken from the behavior of the chicks of a type of bird called See-see partridge. The chicks of this type of bird are located in a regular queue at the time of danger to reach a safe place and they start to move behind their mother to reach a safe point. To simulate the behavior of the chicks of this bird in the form of an optimization algorithm, each chick is considered as a particle of the suboptimal problem. The state of each particle should be according to the behavior of this type of chicks in a regular queue that we know this queue takes us to the best optimal point and this does not mean that



minimizing the search space, but also, it is converging particles after some searches in a regular queue to the best point answers (bird mother). According to Fig. (4), each chick in the search space seeks to find a chick with the priority of a unit higher than itself and it tries to adjust its motion equation based on this chick.

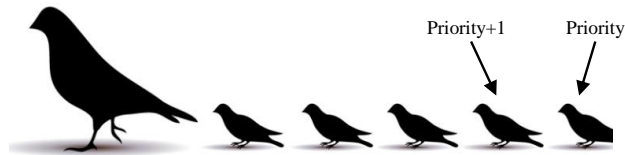


Fig. (4). Chicks motion in proposed algorithm.

The value of priority variable is a number that causes the particles move in a regular convergence line to the global optimum after some moving in the search space.

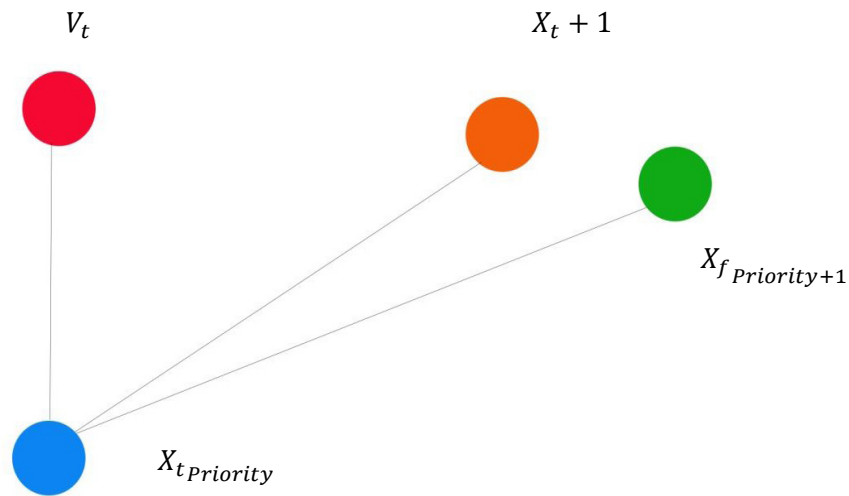


Fig. (5). Particles motion in proposed algorithm.

According to Fig. (5), particle  $t$  for going to new position,  $X_t + 1$ , its velocity equation according to your previous velocity,  $V_t$ , and position of particle  $f$  its priority valuable is one until more than that of the particle. In each iteration of the algorithm, the particle that has a higher priority is located to be the base of other particles and particles adjust their movement based on these particles with higher priority and this automatically causes that the particle with a good optimum has a

higher priority in each iteration and finally, the particle which is at the beginning of the line to the optimum solution will be the mother bird which has the best cost for the algorithm. In fact, the particle that has the best cost is the mother bird. We consider a variable for each particle entitled as priority variable. For particle  $i$ , priority variable defined according to equation 1:

$$X_i.priority \quad (1)$$

In every assessment, when a particle was better than the best personal experience or local optimum; a unit is added to the priority variable of that particle:

$$if \ X_i.cost > P_{best} \rightarrow P_{best} = X_i.position \ and \ X_i.priority = X_i.priority + 1 \quad (2)$$

$X_i.cost$  The cost of each particle in the benchmark,  $P_{best}$  is the best personal experience of each particle, and  $X_i.position$  is the location of each particle. In every time of assessment, if the local optimum is better than the global optimum and vice versa, the particle's priority variable goes higher and a unit is added to it:

$$if \ P_{best} > G_{best} \rightarrow G_{best} = P_{best} \ and \ X_i.priority = X_i.priority + 1 \quad (3)$$

$G_{best}$  is the global optimum. The motion equation of each particle is set almost similar to the particle swarm algorithm in the form of equation 4:

$$X_i.position = X_i.position + X_i.velocity \quad (4)$$

$X_i.velocity$  is the velocity of each particle or chick. Then, Chickens sorted in array based on priority variable. Fig. (6) shows the sorting by priority.

## How to Transform the Behavior in Nature into the Algorithm

**Abstract:** In recent years, recognizing amazing resources in nature can be a way to formulate ideas for optimization problems. First, the ideas are selected in nature, and then the hidden purposeful behavior of these ideas is discovered and expressed as a systematic algorithm. Choosing and observing the order in animals and nature is an art, and researching them is a practical way of analyzing them. The most important part is that these behaviors must be selected in order and then formulated mathematically. This chapter will discuss some techniques for converting ideas into algorithms and a specific framework. Some of the important principles in converting behaviors in nature into mathematical equations are outlined in this chapter. If one can find the best and easiest way to transform an idea into a mathematical equation in the form of an algorithm, then one can claim that an efficient algorithm is presented that can solve a complex problem. If some of the principles outlined in this chapter are followed, a good algorithm can be derived from a natural idea. This chapter introduces examples of nature-inspired algorithms presented by authors in recent years. These algorithms all use the source of nature, and the nature and behavior of some animals are the main basis of these algorithms. These algorithms show the orderly behavior of some natural animals and also show how this targeted order can be transformed into an algorithm. Understanding these algorithms can help the reader understand how to transform the idea of nature into meaningful equations. We present some examples of these algorithms in this chapter to familiarize the reader with the order in some natural animals. Also, in this chapter, we can understand how to transform this natural order into meaningful equations. These meaningful equations are introduced in the form of an optimization algorithm.

**Keywords:** Equations, Formulated, Ideas, Implemented, Mathematical.

Let's first look at some of the algorithms that are inspired by nature with their source of inspiration. These algorithms were later used by researchers in various fields. The source of each was found in nature. These sources have been carefully analyzed by the authors. That order in each source was the main reason for writing the algorithm. Pay close attention to a source and target source system. Understanding this can help you. Table 39 lists some of the nature-inspired algorithms, their source of inspiration, and the idea of algorithm formation.

**Table 39.** Algorithm, source and target system of source for several famous algorithms.

Algorithm	Source	Target System of Source
PSO	Birds	The order of the birds during the mass flight
GA	DNA	Evolved Gene of Natural Creatures
ABC	Bees	Finding food by bees
HS	Musical Instrument	The order of musical notes in playing a music
ICA	Colonization of countries	How the Colony Countries Relate
ACO	Ants	Ants' behavior in finding the optimal path
SSPCO	See-see partridge	Behavior of See-See partridge Chicks at Risk

This is a small part of the algorithms that are inspired by behavior in nature. Now, let's go back and find some of the behaviors that have not yet been addressed in nature, whether in nature itself or in living things in nature.

**Fig. (49).** Intrinsic behavior of a dog.

As in Fig. (49), the behavior of animals called dogs in nature can be interesting. Dog is famous for its loyalty to its owner. There may be many other interesting behaviors in this animal, but we focus on this feature. This loyalty mechanism has become a win-win game for the dog and its owner. So, the two populations come together in evolution to survive in nature. Why and how the dog's intrinsic loyalty and dog owner's interest in it both contribute to life, and this is a way to

achieve a common goal in a system. So, here is a mechanism between two populations that ends in a goal. The secret to this behavior is to be found through the research of biologists and zoologists. It then extended this behavior to the entire population of an algorithm. Maybe this algorithm is probably able to solve the problem using two-to-two populations.



**Fig. (50).** The intellectual evolution of humans using one another.

Human development in science can also be of interest to human beings throughout the world (Fig. 50). What is the reason for how science has changed in different parts of the world over the different years? The science in the world has moved from one point to another point based on a specific mechanism. So one has to research and find out why science and civilization in the world have moved from place to place. Here, the geography of the world can be assumed to be the space of an issue, and science is assumed to be elite populations. The relationship between points that have reached competence over time can lead to a specific mechanism.

## Conclusion

**Abstract:** Nature-inspired algorithm is types of computing systems use a variety of phenomena in nature to create a coherent mechanism. Designing different systems and creating learning machines as well as optimization are some of the factors that have chosen nature. These systems come from nature and have designed interesting mechanisms. The nature of the search problem is very important in nature and the species of animals and even the natural structures each have a kind of search system inherently. In this book, optimization and optimization algorithms are examined, and solutions are proposed to create a nature-inspired optimization algorithm, and even suggestions are made for natural phenomena that can be transformed into algorithms. The sciences, industry, medicine, and other fields can find algorithms that fit their field by reading this book. Collective intelligence is one of the main phenomena found in nature, and this book also emphasized this. This book first describes optimization, then defines the optimization problem and describes its mechanism. Then nature-inspired optimization algorithms were evaluated and a number of them were introduced. The source of nature was then discussed and explained why nature is a good source of ideas for building an algorithm. A number of authors' algorithms were studied to familiarize the reader with these types of algorithms and then ideas of nature were proposed to the reader. Finally, how to convert an idea into an algorithm is discussed.

**Keywords:** Ideas, Nature-inspired, Optimization, Order, Source, Swarm.

Change is one of the things that occur in the system over time and the system needs to adapt to it. Relations and computing some of the issues are so complex that they are beyond human ability. Machine learning is one of the new systems that solve these difficult calculations well. Experience and information are very important in machine learning. Proper and efficient use of this information by these systems can lead to the production of efficient algorithms. Optimization systems today in the field of e-commerce can make an economic revolution in the world. In this book, the goal is for the reader to become familiar with algorithms and learning systems and optimizers. Mathematical Optimization is the branch of mathematics that aims to solve the problem of finding the elements that maximize or minimize a given real-valued function. Many problems in engineering and machine learning can be cast as mathematical optimization problems, which explain the growing importance of the field. For example, in a spam detection

filter we might aim to find the system that minimizes the number of misclassified emails. Similarly, when an engineer designs a pipe, we will seek for the design that minimizes cost while respecting some safety constraints. Both are examples that can be modelled as optimization problems.

The beauty of optimization is that it allows abstracting from the specifics of the particular problem. For example, once we have transformed the spam detection filter and the pipe design the form of a mathematical optimization problem, we can use the same optimization algorithms to them, abstracting the fact that these are, in origin, very different problems.

In this book, optimization was first defined. Then nature-inspired algorithms were reviewed and their sources of inspiration were announced. Some of the author's algorithms, all inspired by nature, were also explored. Some ideas were introduced in nature that is interesting in order to make an algorithm out of them. Finally, the overall idea of constructing an idea in a framework and algorithm was examined. There are so many interesting ideas in nature that researchers can read through the book to learn how to build an algorithm inspired by these ideas. This book was a small attempt to bring new algorithms into the optimization world research cycle.

The book's most relevant concept is that the reader will be able to turn an idea that he observes in nature and is of interest to him, into a single search mechanism. In this book, we do not intend to confront the reader with a scholarly article. We would love to have a practical book, rather than a compilation book. The optimal concept was defined, then nature and natural phenomena were discussed, and even examples were introduced in nature. This introduction to examples of nature is only for the reader to know what exactly a natural idea means. Here are some examples of nature-inspired algorithms where the reader can see exactly how an idea has been turned into an algorithm. And finally, we came up with solutions that consist of the idea-starting scenario of the algorithm. We have come up with ways to formulate the idea. These guidelines were generalized. However, each idea has its own different demographic, the movement of its components is different, and has a different mechanism. So, we discussed in general and covered most of the ideas.

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