



# Chapter 10

## Evolutionary Computation in Artificial Intelligence: Adapting Nature's Strategies for Smart Systems


**Dharmesh Dhabliya**

 <https://orcid.org/0000-0002-6340-2993>  
*Vishwakarma Institute of Information  
Technology, Pune, India*

**Ankur Gupta**

 <https://orcid.org/0000-0002-4651-5830>  
*Vaish College of Engineering, Rohtak, India*

**Sukhvinder Singh Dari**

 <https://orcid.org/0000-0002-6218-6600>  
*Symbiosis Law School, Symbiosis International  
University (Deemed), Pune, India*


**Ritika Dhabliya**

*Yashika Journal Publications Pvt. Limited,  
Wardha, India*

**Anishkumar Dhabliya**

*Altimetrik India Pvt. Ltd., Pune, India*

**Nitin N. Sakhare**

 <https://orcid.org/0000-0002-1748-799X>  
*BRAC'S Vishwakarma Institute of Information  
Technology, Pune, India*

**Rohit Anand**

*G.B. Pant DSEU Okhla-1 Campus, New Delhi,  
India*

### ABSTRACT

*In the realm of robotics and artificial intelligence, researchers often draw inspiration from the intricate and efficient systems found in the animal kingdom. For instance, the study of swarm intelligence, inspired by the collective behavior of insects like ants or bees, has led to the development of algorithms for autonomous drones and robotic systems that can collaboratively solve complex problems. The adaptation of nature's strategies for smart systems showcases the potential for interdisciplinary collaboration between biology and technology. By understanding and emulating the efficiency, adaptability, and sustainability observed in natural systems, scientists and engineers continue to push the boundaries of innovation, creating smart systems that are not only technologically advanced but also environmentally conscious and resilient.*

DOI: 10.4018/979-8-3693-2073-0.ch010

## **1. INTRODUCTION**

Evolutionary Computation (EC) in Artificial Intelligence represents a transformative approach that draws inspiration from nature's evolutionary processes to craft intelligent algorithms for problem-solving. Emulating the principles of natural selection, EC involves the iterative generation, selection, and adaptation of potential solutions within a population, mirroring the way biological systems evolve over generations. This innovative paradigm, encompassing algorithms like Genetic Algorithms and Evolutionary Strategies, has proven particularly adept at tackling complex optimization problems across diverse domains. By adapting nature's strategies of selection, crossover, and mutation, EC enables smart systems to autonomously refine and improve their performance, demonstrating a remarkable ability to discover optimal solutions in large solution spaces (Anand & Chawla, 2020). This bio-inspired methodology holds promise for revolutionizing problem-solving methodologies in artificial intelligence, offering adaptability and efficiency akin to the evolutionary mechanisms (Kala, 2023) observed in the natural world.

Evolutionary Computation (EC) is a subfield of Artificial Intelligence (AI) that draws inspiration from the principles of natural evolution to develop intelligent algorithms and systems (Singh et al., 2022; Raghavan et al., 2022). The fundamental idea behind EC is to mimic the process of natural selection to evolve solutions to complex problems over successive generations. Evolutionary Computation in Artificial Intelligence leverages the principles of natural evolution to create intelligent algorithms capable of solving complex problems. Its versatility and adaptability make it a valuable tool for optimization and learning tasks in various domains.

### **1.1 Evolutionary Computation**

Evolutionary computation (as shown in Figure 1) is an area of AI and soft computing that studies algorithms for global optimization that are based on the theory of biological evolution (Anand & Chawla, 2020; Kala, 2023). To put it more precisely, they are a class of metaheuristic or stochastic optimization-style problem solvers that rely on population-based trial and error. Iteratively updating an initial list of possible solutions is the first step in evolutionary computing. Less desirable solutions are stochastically removed, minor random changes are introduced, and, depending on the approach, parental information is mixed (Anand & Chawla, 2016). Natural selection, also known as artificial selection, mutation, and recombination are processes that occur in biology when a population of solutions is tested. Consequently, the population will undergo progressive evolution in order to improve its fitness, which is specifically the fitness function selected by the algorithm. Evolutionary computing approaches have gained popularity in computer science due to their ability to provide optimal solutions across many problem domains (Anand & Chawla, 2016). There are a plethora of variations and extensions available, each tailored to a different set of issues and data formats. To examine common characteristics of broad evolutionary processes, evolutionary computation is sometimes utilized as an *in silico* experimental approach in evolutionary biology.

When it comes to tackling computational problems, Evolutionary Computation (EC) is at the vanguard, taking its cues from the rules that control evolution in nature. Based on the principle of natural selection, evolutionary complexity (EC) uses a population of possible solutions to difficult problems via repeated cycles of selection, recombination (crossover), and mutation. This method has several uses in optimization, machine learning, artificial intelligence, and other fields since it mimics the evolutionary dynamics seen in biological systems. One of the most well-known subfields of evolutionary computing,

17 more pages are available in the full version of this document, which may be purchased using the "Add to Cart" button on the publisher's webpage:

[www.igi-global.com/chapter/evolutionary-computation-in-artificial-intelligence/344568](http://www.igi-global.com/chapter/evolutionary-computation-in-artificial-intelligence/344568)

## Related Content

---

### Dynamic Links and Evolutionary History in Simulated Gene Regulatory Networks

T. Steiner, Y. Jin, L. Schrammand B. Sendhoff (2010). *Handbook of Research on Computational Methodologies in Gene Regulatory Networks* (pp. 498-522).

[www.irma-international.org/chapter/dynamic-links-evolutionary-history-simulated/38249](http://www.irma-international.org/chapter/dynamic-links-evolutionary-history-simulated/38249)

### Behavioral Biometrics: Categorization and Review

Roman V. Yampolskiy, Nawaf Ali, Darryl D'Souzaand Abdallah A. Mohamed (2014). *International Journal of Natural Computing Research* (pp. 85-118).

[www.irma-international.org/article/behavioral-biometrics/118159](http://www.irma-international.org/article/behavioral-biometrics/118159)

### An Optimized In Silico Neuroinformatics Approach: Positive Regulation via DNA Interaction in Cellular Decisions for Arg to Ala Mutation in SOX11

Arundhati Banerjeeand Sujay Ray (2016). *Handbook of Research on Natural Computing for Optimization Problems* (pp. 802-820).

[www.irma-international.org/chapter/an-optimized-in-silico-neuroinformatics-approach/153841](http://www.irma-international.org/chapter/an-optimized-in-silico-neuroinformatics-approach/153841)

### Lost Student Tracking in an Incomplete and Imprecise Information Environment Using Soft Computing Paradigm

Satya Ranjan Dash, Susil Rayaguru, Satchidananda Dehuriand Sung-Bae Cho (2012). *International Journal of Artificial Life Research* (pp. 32-48).

[www.irma-international.org/article/lost-student-tracking-in-an-incomplete-and-imprecise-information-environment-using-soft-computing-paradigm/101293](http://www.irma-international.org/article/lost-student-tracking-in-an-incomplete-and-imprecise-information-environment-using-soft-computing-paradigm/101293)

### Materialized View Selection using Marriage in Honey Bees Optimization

Biri Arunand T.V. Vijay Kumar (2015). *International Journal of Natural Computing Research* (pp. 1-25).

[www.irma-international.org/article/materialized-view-selection-using-marriage-in-honey-bees-optimization/146882](http://www.irma-international.org/article/materialized-view-selection-using-marriage-in-honey-bees-optimization/146882)