

Chapter 13

Invasive Weed Optimization Algorithm

Abstract In this chapter, we present an interesting algorithm called invasive weed optimization (IWO) which is inspired from colonizing weeds. We first describe the general knowledge of the biological invasion in [Sect. 13.1](#). Then, the fundamentals and performance of IWO are introduced in [Sect. 13.2](#). Finally, [Sect. 13.3](#) summarises this chapter.

13.1 Introduction

Weeds are one of the most robust and troublesome plants in agriculture. When we were young, you may have heard that “the weeds always win”. This is due to the weeds have some strong properties, such as adaptation, robustness, vigorousness, and invasion. Based on those properties, a novel numerical stochastic optimization algorithm called invasive weed optimization (IWO) is proposed by Mehrabian and Lucas (2006) which is based on the natural selection (survival of the fittest) in the biological world.

13.1.1 Biological Invasion

Generally speaking, biological invasion is a phenomenon in which the groups of individuals (such as weeds) migrate to new environments and compete with native populations (Shigesada and Kawasaki 1997). In fact, it is not a novel phenomenon however, it is one of the most important impacts on the earth’s ecosystems (Jose et al. 2013). Also, it can be used as a fundamental framework in designing effective optimization algorithms (Falco et al. 2012).

13.2 Invasive Weed Optimization Algorithm

13.2.1 Fundamentals of Invasive Weed Optimization Algorithm

Invasive weed optimization (IWO) algorithm was originally proposed in Mehrabian and Lucas (2006). To implement the IWO algorithm, the following steps need to be performed (Mehrabian and Lucas 2006; Roshanaei et al. 2008):

- Initialization: a population of initial weeds $W = (w_1, w_2, \dots, w_m)$, each representing one trial solution of the optimization problem at hand, is being dispread over the d -dimensional problem space with random positions.
- Reproduction: each member of the population is allowed to produce seeds depending on its own, as well as the colony's lowest and highest fitness to simulate the natural survival of the fittest process. Such that, the number of seed produced by a weed increases linearly from lowest possible seed for a weed with worst fitness to the maximum number of seeds for a plant with best fitness (which corresponds to the lowest objective function value for a minimization problem).
- Spatial distribution: the generated seeds are being randomly distributed over the d -dimensional search space by normally distributed random numbers with mean equal to zero; but varying variance parameter decreasing over the number of iteration. The reason for that is to guarantee that the produced seeds will be generated in a distant area but around the parent weed and decreases nonlinearly, which results in grouping the fitter plants are together and inappropriate plants are eliminated over times. Here, the standard deviation (σ) of the random function is made to decrease over the iterations from a previously defined initial value ($\sigma_{initial}$), to a final value (σ_{final}), is calculated in every time step via Eq. 13.1 (Mehrabian and Lucas 2006; Roshanaei et al. 2008):

$$\sigma_{iter} = \frac{(iter_{max} - iter)^n}{(iter_{max})^n} (\sigma_{initial} - \sigma_{final}) + \sigma_{final}, \quad (13.1)$$

where $iter_{max}$ is the maximum number of iterations, σ_{iter} is the standard deviation at the present time step and n is the non-linear modulation index usually set as 2.

- Competitive exclusion: due to fast reproduction, after passing some iteration the number of produced plants in a colony reaches to its maximum (P_{max}). In this step, a competitive mechanism is activated for eliminating undesirable plants with poor fitness and allowing fitter plants to reproduce more sees as expected. This process continues until maximum iterations or some other stopping criteria are reached and the plant with the best fitness is selected as the optimal solution.

Taking into account the key phases described above, the steps of implementing the IWO algorithm can be summarized as follows (Ghosh et al. 2011; Roy et al. 2013; Li et al. 2011; Kundu et al. 2012; Mehrabian and Lucas 2006)

- Step 1: Initialize randomly generated weeds in the entire search space.
- Step 2: Evaluate fitness of the whole population members.
- Step 3: Allow each population member to produce a number of seeds with better population members produce more seeds (i.e., reproduction).
- Step 4: The generated seeds are distributed over the search space by normally distributed random numbers with mean equal to zero but varying variance (i.e., spatial dispersal).
- Step 5: When the weed population exceeds the upper limit, perform competitive exclusion.
- Step 6: Check the termination criteria.

13.2.2 Performance of IWO

In order to test the performance of IWO, a set of benchmark multidimensional functions are adopted in Mehrabian and Lucas (2006), such as Sphere function, Griewank function and Rastrigin function. Compared with other CI algorithms [such as genetic algorithm (GA), simulated annealing (SA), and particle swarm optimization (PSO)], computational results showed that IWO is capable of finding desired minima very fast.

13.3 Conclusions

Recently, there has been a considerable attention paid for employing nature inspired algorithms to solve optimization problems. Among others, IWO is a new member that motivated by a common phenomenon in agriculture, i.e., colonization of invasive weeds. Although it is a newly introduced CI method, we have witnessed the following rapid spreading of IWO:

First, several enhanced versions of IWO can be found in the literature as outlined below:

- Cooperative coevolutionary IWO (Hajimirsadeghi et al. 2009).
- Differential IWO (Basak et al. 2013).
- Differential IWO (Basak et al. 2013).
- Discrete IWO (Ghalenoiei et al. 2009).
- Foraging weed colony optimization (Roy et al. 2010).
- Hybrid IWO and differential evolution algorithm (Roy et al. 2013).
- IWO for multiobjective optimization (Kundu et al. 2012).
- Modified IWO (Giri et al. 2010; Ghosh et al. 2011; Pahlavani et al. 2012; Basak et al. 2010).
- Non-dominated sorting IWO (Nikoofard et al. 2012).

Second, the IWO algorithm has also been successfully applied to a variety of optimization problems as listed below:

- Antenna design optimization (Roshanaei et al. 2008; Mallahzadeh et al. 2009; Basak et al. 2010; Li et al. 2011; Mallahzadeh and Taghikhani 2013).
- Communication scheme optimization (Hung et al. 2010).
- Control optimization (Ghosh et al. 2011).
- Data clustering (Mehrabian and Lucas 2006).
- Electricity market optimization (Hajimirsadeghi et al. 2009; Nikoofard et al. 2012).
- Feed-forward neural network training (Giri et al. 2010).
- Multimodal optimization (Roy et al. 2013).
- Multiple task allocation problem (Ghalenoei et al. 2009).
- Recommender system optimization (Rad and Lucas 2007).
- Solving nonlinear equations (Pourjafari and Mojallali 2012).
- Travel path optimization (Pahlavani et al. 2012).

Interested readers please refer to them as a starting point for a further exploration and exploitation of the IWO algorithm.

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