

A Nature-Inspired Metaheuristic Approach for Generating Alternatives

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INTRODUCTION

Decision-making in the “real world” involves complex problems that tend to be riddled with competing performance objectives and possess requirements which are very difficult to incorporate into any underlying decision support models (Brugnach, Tagg, Keil, De Lange, 2007; Janssen, Krol, Schielen, Hoekstra, 2010; Mowrer, 2000; Walker, Harremoes, Rotmans, Van der Sluis, Van Asselt, Janssen, Krayen von Krauss, 2003). While an optimal solution might provide the theoretically best answer to a mathematical model, in general, it will not be the best solution to the fundamental “real” problem since there are invariably unmodelled objectives and unquantifiable issues not incorporated in the problem formulation (Brugnach *et al.*, 2007; Gunalay, Yeomans, 2012; Gunalay, Yeomans, Huang, 2012; Janssen *et al.*, 2010; Loughlin, Ranjithan, Brill, Baugh, 2001). Consequently, it is preferable to generate a number of different alternatives that provide multiple, disparate perspectives to any particular problem (Imanirad, Yeomans, 2014; Matthies, Giupponi, Ostendorf, 2007; Yeomans, Gunalay, 2011). Preferably these alternatives should all possess good (i.e. near-optimal) objective measures with respect to the modelled objective(s), but be as fundamentally different as possible from each other in terms of the system structures characterized by their decision variables (Yeomans, 2011).

To address this option creation need, several approaches collectively referred to as *modelling-to-generate-alternatives* (MGA) have been developed (Loughlin *et al.*, 2001; Yeomans, Gunalay, 2011; Yeomans, 2012). The principal motivation

for MGA is to create a small set of alternatives that are as maximally different from each other in the decision space as possible, yet are still considered “good” with respect to all of the modelled objective(s) (Yeomans, 2011; Yeomans, 2012). By adopting a maximally different method, the resulting alternative solution set is likely to provide very different perspectives with respect to any unmodelled issues, while simultaneously providing different choices that all perform somewhat similarly with respect to the modelled objectives (Gunalay, Yeomans, 2012; Gunalay *et al.*, 2012; Walker *et al.*, 2003; Yeomans, 2011).

In this chapter, it is shown how a modified version of the metaheuristic Firefly Algorithm (FA) of Yang (2009; 2010) can be used to efficiently generate a set of maximally different solution alternatives. Yang (2010) has demonstrated that, for optimization and calculational purposes, the FA is more computationally efficient than the more commonly-employed enhanced particle swarm, genetic algorithm, and simulated annealing metaheuristic procedures. Thus, this FA-based MGA procedure can be considered very computationally efficient (Imanirad, Yeomans, 2014). This demonstrates the MGA proficiencies of the FA-based approach for constructing multiple, maximally different solution alternatives to the highly non-linear optimization problem of Loughlin *et al.* (2001).

BACKGROUND

While this section provides a brief synopsis of the steps involved in the FA process, more specific details can be found in Yang (2009; 2010). The

Algorithm 1.

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Objective Function  $F(\mathbf{X})$ ,  $\mathbf{X} = (x_1, x_2, \dots, x_d)$ 
Generate the initial population of  $n$  fireflies,  $\mathbf{X}_i$ ,  $i = 1, 2, \dots, n$ 
Light intensity  $I_i$  at  $\mathbf{X}_i$  is determined by  $F(\mathbf{X}_i)$ 
Define the light absorption coefficient  $\gamma$ 
while ( $t < \text{MaxGeneration}$ )
    for  $i = 1: n$ , all  $n$  fireflies
        for  $j = 1: n$ , all  $n$  fireflies (inner loop)
            if ( $I_i < I_j$ ), Move firefly  $i$  towards  $j$ ; end if
            Vary attractiveness with distance  $r$  via  $e^{-\gamma r^2}$ 
        end for  $j$ 
    end for  $i$ 
    Rank the fireflies and find the current global best solution  $\mathbf{G}^*$ 
end while
Postprocess the results

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FA is a nature-inspired, population-based meta-heuristic that employs the following three idealized rules: (i) All fireflies within a population are unisex, so that one firefly will be attracted to other fireflies irrespective of their sex; (ii) Attractiveness between fireflies is proportional to their brightness, implying that for any two flashing fireflies, the less bright one will move towards the brighter one. Attractiveness and brightness both decrease as the distance between fireflies increases. If there is no brighter firefly within its visible vicinity, then a particular firefly will move randomly; and (iii) The brightness of a firefly is determined by the landscape of the objective function. Namely, for a maximization problem, the brightness can simply be considered proportional to the value of the objective function. Based upon these three rules, the basic operational steps of the FA are summarized within the pseudo-code of Algorithm 1 Yang (2010).

In the FA, there are two important issues to resolve: the variation of light intensity and the formulation of attractiveness. For simplicity, it can always be assumed that the attractiveness of a firefly is determined by its brightness which in turn is associated with the encoded objective function. In the simplest case, the brightness of a firefly at a particular location \mathbf{X} would be its

calculated objective value $F(\mathbf{X})$. However, the attractiveness, β , between fireflies is relative and will vary with the distance r_{ij} between firefly i and firefly j . In addition, light intensity decreases with the distance from its source, and light is also absorbed in the media, so the attractiveness should be allowed to vary with the degree of absorption. Consequently, the overall attractiveness of a firefly can be defined as

$$\beta = \beta_0 \exp(-\gamma r^2)$$

where β_0 is the attractiveness at distance $r = 0$ and γ is the fixed light absorption coefficient for a specific medium. If the distance r_{ij} between any two fireflies i and j located at \mathbf{X}_i and \mathbf{X}_j , respectively, is calculated using the Euclidean norm, then the movement of a firefly i that is attracted to another more attractive (i.e. brighter) firefly j is determined by

$$\mathbf{X}_i = \mathbf{X}_i + \beta_0 \exp(-\gamma(r_{ij})^2)(\mathbf{X}_i - \mathbf{X}_j) + \alpha \mathbf{e}_i.$$

In this expression of movement, the second term is due to the relative attraction and the third term is a randomization component. Yang (2010) indicates that the randomization parameter, α , is normally selected within the range $[0,1]$ and \mathbf{e}_i is

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