

Bio-Inspired Modelling to Generate Alternatives

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INTRODUCTION

Typical “real world” decision-making applications involve complex problems that possess requirements which are very difficult to incorporate into supporting decision models and tend to be riddled with competing performance objectives (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 optimal solutions provide the mathematically best answers to the modelled problems, they are generally not the best solutions to the underlying real problems as there are invariably unquantifiable issues and unmodelled objectives not apparent at the time of model construction (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 the particular problem (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).

In response to this option creation requirement, several approaches collectively referred to as *modelling-to-generate-alternatives* (MGA) have been developed (Loughlin *et al.*, 2001;

Yeomans, Gunalay, 2011; Yeomans, 2012). The primary motivation behind MGA is to produce a manageably small set of alternatives that are good with respect to known modelled objective(s) yet are maximally different from each other in the decision space (Yeomans, 2011; Yeomans, 2012). In so doing, the resulting alternative solution set is likely to provide truly different choices that all perform somewhat similarly with respect to the modelled objectives, yet provide very different perspectives with respect to any unmodelled issues (Gunalay, Yeomans, 2012; Gunalay *et al.*, 2012; Walker *et al.*, 2003; Yeomans, 2011).

In this chapter, it is shown how to efficiently generate a set of maximally different solution alternatives by implementing a modified version of the new metaheuristic Firefly Algorithm (FA) of Yang (2009; 2010). For calculation and optimization purposes, Yang (2010) has demonstrated that the FA is more computationally efficient than such commonly-used metaheuristics as genetic algorithms, simulated annealing, and enhanced particle swarm optimization. Hence, this innovative MGA procedure using the FA is very computationally efficient. This study illustrates the efficacy of the MGA capabilities of this new FA approach for constructing multiple, maximally different solution alternatives to the bivariate Michalewicz function test problem (Cagnina, Esquivel, Coello, 2008; Yang, Deb, 2010) and to a well-known standard constrained engineering optimization problem (Aragon, Esquivel, Coello, 2010; Cagnina *et al.*, 2008).

DOI: 10.4018/978-1-4666-5202-6.ch033

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 FA is a nature-inspired, population-based metaheuristic that employs the following three idealized rules:

1. All fireflies within a population are unisex, so that one firefly will be attracted to other fireflies irrespective of their sex;
2. 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
3. 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 Yang (2010) presented in Box 1.

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 X would be its calculated objective value $F(X)$. 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

Box 1. Pseudo code of the Firefly Algorithm

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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  $G^*$ 
end while
Postprocess the results

```

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