Closure to "Modified Firefly Algorithm for Solving Multireservoir Operation in Continuous and Discrete Domains" by Irene Garousi-Nejad, Omid Bozorg-Haddad, and Hugo A. Loáiciga

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The discusser highlighted some opportunities to clarify a few aspects of the writers' paper. The main argument of the discussion is that the modification presented in the original paper cannot assure proper algorithmic parameter tuning. It is factual that tuning the parameters of an evolutionary or metaheuristic algorithm in a manner that is suitable for all optimization problems is not possible. The original paper did not claim that the modified version of the firefly algorithm (MFA) can handle algorithmic parameter tuning simultaneously with near-global optimization. The MFA starts by generating a random matrix of solutions whose dimensions equal the product of the population size times the number of decision variables. This matrix is generated considering the acceptable range of each of the decision variables. This matrix is updated iteratively by the MFA using two operators, called exploitation and exploration functions (Aboutalebi et al. 2015b; Garousi-Nejad et al. 2016). The genetic algorithm (GA), for instance, implements exploitation and exploration functions with the crossover and mutation functions, respectively. The iterative improvement of the matrix of solutions ends with a near-global solution of the optimization problem being solved. The parameters of the MFA are not subjected to tuning during an optimization run.

The discusser asserted in "FA and Its Parameter Selection" section that Gandomi et al. (2013) reported that the FA may converge to local optima. The discusser further argued that the modification step in the MFA proposed by the writers does not remedy the convergence to local optima. It is known, however, that the exploration function of MFA prevents it from becoming entrapped in local optima [discussions of this matter have been conducted by Aboutalebi et al. (2015a) and Garousi-Nejad et al. (2016)].

The discusser asserted that the FA is sensitive to its parameters. The discusser ran the FA for a problem with various combinations of the algorithmic parameters and reported that the FA generated objective function values ranging between 283 and 293. This is not surprising given that the FA in particular, and evolutionary algorithms in general, are random in nature and each run produces a different value of the objective function even when the algorithmic parameters are kept constant. This is the reason why one must run the MFA repeatedly with fixed parameters to characterize their solutions in terms of the average of several runs, with a dispersion measured by the standard deviation of solutions (Aboutalebi et al. 2016a). The "How Proposed Modifications in the Original Paper Affect Parameter Tuning" section in the discussion claimed that the writers proposed the MFA to cope with the limitations of FA, primarily tuning its parameters. However, the writers did not intend to modify the FA to be self-tuning. Instead, the advantages of the MFA were (1) reaching solutions that are equal to the global optimum achieved with linear programming (LP); (2) identifying different alternative optimal solutions that had not been reported by other researchers; and (3) updating the exploration function to increase the convergence speed of the FA and avoid local optima.

The "Contribution of the MFA" section of the discussion states that most metaheuristic or evolutionary algorithms have similar performance, and the major difference among them is mainly semantic. The latter statement has been disproved by several studies that have shown the improvements in the objective function achieved by suitable algorithmic modifications (Aboutalebi and Bozorg-Haddad 2015; Aboutalebi and Garousi-Nejad 2015; Aboutalebi et al. 2016b). For instance, the particle swarm optimization (PSO) algorithm introduced by Kennedy and Eberhart (1995) was modified by Shi and Eberhart (1998) by adding a random weight to the original equation of PSO. This was a successful improvement that generated over 10,000 citations. Therefore, seemingly simple improvements to evolutionary algorithms might lead to significant improvements in their performance. This was demonstrated in the original paper via the improvement made to the FA.

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