Supplementary material for Zheng *et al.*, "A novel experience-based learning algorithm for structural damage identification: simulation and experimental verification", *Engineering Optimization*, 2019.

Conceptual comparative analysis of EBL with other metaheuristic algorithms

Broadly, all nature-inspired metaheuristics algorithms give a similar appearance superficially and are generally differentiated on the basis of their solution updating strategy (Jain *et al.* 2018). In the section, a brief conceptual comparative analysis of EBL is conducted in this section with respect to teaching-learning-based optimization (TLBO), lightning attachment procedure optimization (LAPO) and squirrel search algorithm (SSA).

1 Teaching-learning-based optimization

TLBO is a nature-inspired algorithm based on the effect of a teacher on learners. The process of TLBO consists of the 'Teacher Phase' and the 'Learner Phase' phases.

In the "Teacher phase" of TLBO, the existing solution is modified by (Rao *et al.* 2011):

$$X_i^{new} = X_i^{old} + rand \cdot (M_{new} - T_F M_i) \tag{1}$$

where T_F is a teaching factor that decides the value of mean to be changed, $rand$ is a random number in the range [0, 1], M_i is the mean at any iteration, the teacher T_i try to move mean M_i towards its own level, and M_{new} is the new mean.

In the "Learner phase" of TLBO, a learner X_i learns something new if the other learner X_j has more knowledge than him or her, and the learner modification is given as follows (Rao *et al.* 2011):

$$X_i^{new} = \begin{cases} X_i^{old} + rand \cdot (X_i - X_j), if \;\; f(X_i) < f(X_j) \\ X_i^{old} + rand \cdot (X_j - X_i), \qquad\qquad otherwisre \end{cases} \tag{2}$$

Although both TLBO and EBL generate new solutions through learning message from other candidates, their learning formulation and updating mechanism are technically different. Moreover, TLBO updates all solutions in the pattern matrix by a single mode; while EBL employs two modes.

2 Lightning attachment procedure optimization

LAPO is a nature-inspired optimization algorithm inspired by the lightning attachment procedure including the downward and the upward leader movements.

In the downward leader movement of LAPO, for test point *i*, a random point *j* is selected among the population (*i* ≠ *j*) as the potential next jump points (Nematollahi *et al.* 2017):

$$X_{new}^i = \begin{cases} X_{new}^i + rand(X_{ave} - rand \cdot X_{potentialpoint}^j), if \;\; F_{ave} < F^j \\ X_{new}^i - rand(X_{ave} - rand \cdot X_{potentialpoint}^j), otherwisre \end{cases} \tag{3}$$

$$X_{ave} = mean(X_{testpoint}) \tag{4}$$

In the upward leader movement of LAPO, the next trajectory of a test point as an upward leader is formulated as follows (Nematollahi *et al.* 2017):

$$X_{testpoint\_new} = X_{testpoint\_new} + rand \cdot S \cdot (X_{min} - X_{max}) \tag{5}$$

$$S = 1 - \left(\frac{t}{t_{max}}\right) \cdot exp\left(\frac{t}{t_{max}}\right) \tag{6}$$

where t is the number of iteration, and t_{max} is the maximum number of iterations.

The movement mechanisms EBL and LAPO are different. LAPO generates new positions in the downward leader movement based on a potential point and the average of all test points, and generate new positions in the upward leader movement based on the best point and the worst point. In EBL, candidates are considered to move to a better position around their own initial positions according to a learning strategy based on experience of other solutions.

3 Squirrel search algorithm

SSA mimics the dynamic foraging behavior of southern flying squirrels via gliding, an effective mechanism used by small mammals for travelling long distance in deciduous forest of Europe and Asia. Three scenarios may appear during the dynamic gliding process of flying squirrels.

Scenario 1: Flying squirrels on acorn nut trees $\mathrm{FS_{at}}$ tend to move towards hickory nut tree $\mathrm{FS_{ht}}$. The new locations can be generated as follows (Jain *et al.* 2018):

$$FS_{at}^{new} = \begin{cases} FS_{at}^{old} + d_g G_c\left(FS_{ht}^{old} - FS_{at}^{old}\right), if \ \ R_1 \geq P_{dp} \\ random \ \ location, \qquad\qquad otherwise \end{cases} \tag{7}$$

where d_g is random gliding distance, R_1 is a function which returns a value from the uniform distribution on the interval [0, 1], and G_c is a gliding constant.

Scenario 2: Some squirrels which are on normal trees FS_{nt} may move towards acorn nut FS_{at} to fulfill their daily energy needs. The new locations can be generated as follows (Jain *et al.* 2018):

$$FS_{nt}^{new} = \begin{cases} FS_{nt}^{old} + d_g G_c\left(FS_{at}^{old} - FS_{nt}^{old}\right), if \ \ R_2 \geq P_{dp} \\ random \ \ location, \qquad\qquad otherwise \end{cases} \tag{8}$$

where R_2 is a function which returns a value from the uniform distribution on the interval [0, 1].

Scenario 3: Some flying squirrels on normal trees FS_{nt} may move towards hickory nut tree FS_{ht} assuming that they have already fulfilled their daily energy requirements. In this scenario, the new location of squirrels can be generated as follows

(Jain *et al.* 2018):

$$FS_{nt}^{new} = \begin{cases} FS_{nt}^{old} + d_g G_c\left(FS_{ht}^{old} - FS_{nt}^{old}\right), if \;\; R_3 \geq P_{dp} \\ random \;\; location, \qquad\qquad\qquad otherwise \end{cases} \tag{9}$$

where R_3 is a function which returns a value from the uniform distribution on the interval [0, 1].

In SSA, the flying squirrels are divided into three regions and the movement of flying squirrels in each region is directed by globally best flying squirrels FS_{ht} and FS_{at} using different strategies. In EBL algorithm, the pattern matrix updates by using two modes randomly (Eqs (10)-(12)).

References

Jain, M., V. Singh, and A. Rani. 2019. "A novel nature-inspired algorithm for optimization: Squirrel search algorithm." *Swarm and evolutionary computation* 44: 148-175. doi: 10.1016/j.swevo.2018.02.013.

Nematollahi, A. F., A. Rahiminejad, and B. Vahidi. 2017. "A novel physical based meta-heuristic optimization method known as Lightning Attachment Procedure Optimization." *Applied Soft Computing* 59: 596-621. doi: 10.1016/j.asoc.2017.06.033.

Rao, R. V., V. J. Savsani, and D. P. Vakharia. 2011. "Teaching–learning-based optimization: A novel method for constrained mechanical design optimization problems." *Computer-Aided Design* 43(3): 303-315. doi: 10.1016/j.cad.2010.12.015.