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A Novel Implementation of Nature-inspired Optimization for Civil Engineering: A Comparative Study of Symbiotic Organisms Search 9

Prayogo, D. 1*, Cheng, M.Y. 2, and Prayogo, H.

1

Abstract: The increasing numbers of design variables and constraints have made many civil engineering problems significantly more complex and difficult for engineers to resolve in a timely manner. Various optimization models have been developed to address this problem. The present paper introduces Symbiotic Organisms Search (SOS), a new nature-inspired algorithm for solving civil engineering problems. SOS simulates mutualism, commensalism, and parasitism, which are the symbiotic interaction mechanisms that organisms often adopt for survival in the ecosystem. The proposed algorithm is compared with other algorithms recently developed with regard to their respective effectiveness in solving benchmark problems and three civil engineering problems. Simulation results demonstrate that the proposed SOS algorithm is significantly more effective and efficient than the other algorithms tested. The proposed model is a promising tool for assisting civil engineers to make decisions to minimize the expenditure of material and financial resources. 1

Keywords: Constrained optimization; nature-inspired; symbiotic organisms search; symbiotic relationship.

Introduction In recent decades, design optimization has become a critical and challenging activity that has gained in importance in the 35

field of civil engineering. A goal of designers is to obtain optimal solutions in order to reduce construction project costs. Optimization allows designers to create better designs that reduce expenditures of material and financial resources as well as time. However, modern engineering design problems have increased tremendously in complexity and now frequently address complicated objective functions with large numbers of design variables and constraints [1]. This complexity has inspired numer- ous studies worldwide with the shared goal of developing a model that effectively optimizes current civil

engineering problems. Many optimization methods have been introduced over the 18

past four decades. Gradient-based methods were the first of these methods to be widely used in solving decision-making problems in civil engineer- ing [2].

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@petra.ac.id Note: Discussion is expected before June, 1st 2017, and will be published in the "Civil Engineering Dimension", volume 19, number 2, September 2017. Received 19 January 2017; revised 18 February 2017; accepted 11

04 March 2017. These methods are often inadequate in dealing with the complexities inherent in many of today's optimization problems due to poor handling of large- scale variables and constraints. Additionally, these methods also use analyses

that require gradient information to improve initial solutions. However, 2

the designers usually have insufficient knowledge to locate the initial solutions, as they have no way to identify the most promising area for the global optimum of the current problem. Therefore, these gradient-based search methods frequently fail to converge on global optimum because of failed guesswork in defining the area of the global optimum. The above concerns have encouraged researchers to work to develop better optimization models. The field of nature-inspired algorithms has been studied extensively with regard to its potential to solve optimization problems due to its superior performance in handling models that are highly nonlinear and complex.

One of the most significant advantages of nature-inspired algorithms is 34

that these algorithms do not use gradients to explore and exploit the problem search space. Instead, they combine natural pattern rules and randomness to identify near-optimum solutions efficiently [3]. Examples of nature-inspired algorithms include: Genetic Algorithm

(GA) [4], Particle Swarm Optimization (PSO) [5], Differential Evolution (DE) [6], and Artificial Bee Colony (ABC) [7]. 20

In recent years, numerous studies have proposed nature-inspired approaches to 42

solve civil engineering problems. In construction management,

nature- inspired algorithms have been used to solve problems 19

such as project site layout [8], time-cost trade-off [9], and resource leveling [10]. In structural engineering, examples of nature-inspired appli- cations include: truss design [11,12] and frame design [13]. Nature-inspired algorithms have also been used in dealing with geotechnical problems [14], pavement engineering [15], and concrete mix design [16,17]. As civil engineering

problems become more complex, new nature-inspired algorithms will continue to emerge. 10

A new nature-inspired algorithm called Symbiotic Organisms Search (SOS) 19

has been developed by

Cheng and Prayogo [18]. The SOS algorithm mimics the interactive 4

behavior between living **organisms in**

ecosystem. In the previous study, the performance of SOS has been compared with other nature-inspired techniques in numerous mathematical test functions and engineering problems. The comparison results indicate that SOS was able to achieve a

better performance in terms of effectiveness **and** efficiency [18]. **As** 43

a new nature-inspired algorithm, it is worthwhile to explore and investigate the SOS algorithm in seeking the global solution. This paper studies the effectiveness of Symbiotic Organisms Search (SOS) in solving various civil engineering optimization. SOS is first validated on benchmark functions and then tested on three practical civil engineering problems. The obtained

results are then **compared with well-known optimization** techniques. **The** 39

Symbiotic Organisms Search (SOS) **Symbiotic Organisms Search (SOS)** Algorithm SOS **is a new** nature-inspired **algorithm** inspired **by** 23

the natural phenomena of symbiotic interactions proposed by Cheng and Prayogo [18]. Over the past years, SOS has been proven to successfully solve various problems in different fields of research [19- 22]. In surviving environmental change, the living organisms often develop symbiotic interactions among themselves. The most common examples of symbiotic interactions found in nature

may be divided into three main categories: 1. Mutualism: This **category** 33

describes the interac- tive behavior between two different living orga- nisms that gain advantage mutually from that interaction. An

example of mutualism is the rela- tionships **between oxpecker and zebra.** 6

Oxpecker lands on zebra, eating all the parasites. This activity benefits both zebra and oxpecker, since oxpecker collects foods and zebra gains pest con- trol. Another example of mutualism is the relationship between bee and flower. 2. Commensalism: This category describes the interactive behavior

between two different living organisms **in which one** gains advantage **and the other is unaffected or neutral.** 2

An example of commensalism is the relationships between remora and shark. The remora 2

gains an advantage by attaching

itself to the shark and eats food leftovers. 2

The

shark is unaffected by remora fish activities and 2

gains no benefit from the relationship. Another example of commen- salism is the relationship between orchid and tree. 3. Parasitism: This category describes the interac- tive behavior

between two different living organisms in which one gains advantage 38

and the other is harmed. The anopheles mosquito trans- mits the plasmodium parasite into the human host. The parasite, thus,

reproduces inside the body resulting the human host suffers malaria. 2

Other examples of parasitism is the relationship between cuckoo and reed warbler. In SOS algorithm, three phases of the search are performed mimicking the three symbiotic interac- tions namely mutualism, commensalism, and parasi- tism phase.

By performing these three phases, SOS attempts to move a population (ecosystem) of possible solutions to 6

a better region

in the search space during the searching process for the optimal solution. In SOS, 2

each solution in the population is known as an organism. Every organism

is associated with its fitness value, which 2 represents the survival advantage within the current environment. Through successive iterations, the fitness values of the organisms are improved by simulating the symbiotic interactions. The process of generating solutions through three phases is repeated until stopping criteria are satisfied. The source code for a MATLAB implementation of SOS is publicly available at http://140.118.5.71/sos/. The

next section provides further details on the three phases. Mutualism Phase The **mutualism** 2

phase simulates the mutualism between two living organisms, ecoi and ecoj. The mechanism of mutualism is modeled in Equations (1) - (5). ecomutual ? ecoi ? eco j 2 (1)

BF1 = 1 + round (rand (0,1)) (2) **BF2 = 1 + round (rand (0,1))** 4

(3) ecoi new = ecoi + rand (0,1) * (ecobest – ecomutual * BF1) (4) ecoj new = ecoj + rand (0,1) * (ecobest – ecomutual * BF2) (5) Prayogo, D. et al../

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where ecoi is the i-th organism of the ecosystem, ecoj

is the j-th organism **of the** ecosystem where j ≠ **i,** BF1 **is** 37

the benefit factor matched to ecoi, BF2 is the benefit factor matched to ecoj, ecobest represents the best organism in the current iteration, ecomutual repre- sents the relationship characteristic between orga- nism ecoi and ecoj, ecoi new and ecoj new represent candi- date solutions for ecoi and ecoj after their mutualistic interaction, respectively. ecobest is the target point for every organism to increase its fitness during its interaction with another organism. Organisms ecoi and ecoj are updated only if their new (ecoi new and ecoj

new) fitness is better than their old **fitness** 4

(ecoi and ecoj). Commensalism Phase The commensalism phase simulates the commensal- lism between two living organisms, ecoi and ecoj with ecoi gains advantage and ecoj is unaffected. The mechanism of commensalism is modeled in Equation (6). ecoi new = ecoi + rand(-1,1) * (ecobest – ecoj) (6) where ecoi is the i-th organism of the ecosystem, ecoj is the j-th organism of the ecosystem where j ≠ i, ecoi new represents candidate solutions for ecoi after their interaction, respectively. Organism ecoi

is updated only if its new fitness is better than its old **fitness.** 2

Parasitism Phase The parasitism phase simulates the parasitism between two living organisms, ecoi and ecoj with ecoi gains advantage and ecoj is harmed. Organism ecoi serves a role

similar to the anopheles mosquito and, thus, create **an artificial parasite** 6

called ecoparasite. Generally speaking, ecoparasite is a clone of organism ecoi. To differentiate the ecoparasite from ecoi, some random

decision variables from the initial ecoparasite will be **modified randomly.** 4

The location of the modi- fied decision

variables is determined randomly **using a random** 4

method. For each dimension,

a uniform random number is generated. If the random number is less than 0.5, the variable will be **modified** 4

by a random value generated by uniform distribution; otherwise, it will stay the same. Organism ecoj serves as a host to the ecoparasite. If ecoparasite

has a better fitness value, it kills organism ecoj **and** replaces **its position in the ecosystem. If the fitness value of** ecoj **is better,** 4

ecoj survives and the ecoparasite can

no longer exist in the ecosystem. The Framework of the **SOS Algorithm** for **the** 6

Design Optimization in Civil Engineering Design objectives in design problems also have various other constraints including deflection, stress, material dimensions, pressure, and temperature. Many civil engineering problems may be expressed as constrained optimization problems. This paper handles the constraints using Deb's feasibility rules [23]. The use of SOS in constrained optimization problems that incorporate Deb's rules is summarized as follows. Initialize Ecosystem The SOS establishes an initial ecosystem by gene- rating a matrix that contains uniform random numbers that exist within the given boundaries. After the initialization is complete, the initial best solution is calculated. The ecosystem is expressed as follows: ? eco1 ? x1.1 ? x ? eco ? ? ? ? ? ? 1.D ? ? ? ? ? ? ? ? ? ??eco ecosize?? ??xecosize1, ? xecosize,D?? ? In this step, the initial ecobest is determined by choos- ing the fittest organism in the initial ecosystem. Simulate Interaction between Organisms through the Mutualism Phase After the ecosystem initialization, each organism in the ecosystem will go through three phases,

mutualism, commensalism, and parasitism. In the 6

mutualism phase, ecoj is picked

randomly from the ecosystem that **is** designated **to interact with** ecoi where **i** 6

is start from 1, 2, 3, … to ecosize, j is a random number which ≠ i. New candidate solutions ecoi new and ecoj new are calculated using Equations (2) and (3), in which ecomutual is determined using Equation (1) and Benefit Factors (BF1 and BF2) are determined using Equations (4) and (5). New candidate solutions ecoi new and ecoj new are compared to the old ecoi and ecoj. Deb's rules are implemented to retain

the fittest solutions **in the search space** 17

for the next iteration. Simulate Interaction between Organisms through the Commensalism Phase In the

commensalism phase, another **organism,** ecoj, **is** picked **randomly from the ecosystem to interact with** ecoi. **The** 17

new candidate solution ecoi new is calcu- lated using Equation (6) and compared to the older ecoi. Deb's feasibility rules are applied to identify the fittest organism as the solution to be carried forward into the next iteration. Simulate Interaction between Organisms through the Parasitism Phase In the parasitism phase, another organism, ecoj, is picked randomly from the ecosystem to be a host organism. ecoparasite is created by mutating the parent organism ecoi in random dimensions using distri- buted random numbers that are limited within a specific range. Deb's rules are then used to compare this vector to host organism ecoj. If the host organism is fitter than ecoparasite, the host organism will survive to the next iteration and ecoparasite will be eliminated. Conversely, a fitter ecoparasite will lead to its retention into the next iteration and elimination of ecoj. Updating the Best Organism When the fitness of the organism ecoi is better than the fitness of the ecobest, the ecobest is updated with ecoi. Termination If the current ecoi is not the last member of the ecosystem, the SOS will automatically select the next organism to simulate the mutualism, commen- salism, and parasitism, and update the ecobest. After all members of the ecosystem finish the whole process, SOS will check the termination criteria. The common termination criteria used in the literature

are the maximum **number of iterations and the** maximum **number of** 18

function evaluations. SOS will

stop if one of the termination criteria is reached; otherwise, 2

SOS will start the new iteration. Practical Examples on Civil Engineering Pro- blems This section uses three widely used civil engineering problems to assess SOS performance. Obtained

SOS optimization results are then **compared to data published in the literature.** 2

These problems are: (1) reinforced concrete beam design minimization, (2) 25-bar transmission tower truss weight minimiza- tion, and (3) site layout optimization for caisson structure fabrication. Reinforced Concrete Beam Design Minimiza- tion This case study is a cost minimization

problem of the **reinforced concrete beam as** illustrated **in Figure** 1. **This** 28

was first

presented by Amir and Hasegawa [24]. **The beam is assumed simply supported with a** 22

9.144-m

(30-ft) span **and** subject **to a live load of** 32

1 ton

(2.0 klbf) and a dead load of 8

0.5 ton (1.0 klbf)

accounting for the beam weight. Concrete compres- sive **strength** 15

(?c) and reinforcing steel yield stress (?y) is 34.474 MPa (5 ksi) and 344.74 MPa (50 ksi), respectively. The unit cost of steel and concrete are $472.4/m2/ linear m ($1.0/in2/linear ft) and $9.449/- m2/linear m ($0.02/in2

/linear ft), respectively. **The cross sectional area of reinforcing (As),** beam **width** (b), and **beam depth** 15

(h) are selected as the decision variables. Figure 1. Reinforced Concrete Beam Problem

As is determined **as a discrete variable** and **must be chosen from the** 8

following list: As = [6.0, 6.16, 6.32, 6.6, 7.0, 7.11, 7.2, 7.8, 7.9, 8.0, 8.4] in2; b is determined as an integer variable: b = [28, 29, 30, … , 39, 40] in; and h is a continuous variable with the boundary limit: 5 ≤ h ≤ 10 in. The structure should be designed to meet the mini- mal

strength required under ACI 318-77 **building code: As?** y **M u ? 0.** 3

9 As? y (0.8)(1.0 ? 0.59 0.8bh? c) ?

1.4M d ? 1. 7M **l** (7) **where Mu, Md, and Ml,** respectively, **are the flexural strength, dead load, and live load moments of the beam. In this case, Md** 8

= 152.53 kNm (1350 in kip) and Ml = 305.06 kNm

(2700 in kip). Beam depth ratio is restricted to be less than or equal to 4. The optimization problem may be stated as: Minimize: f (As , **b, h) ? 29.** 4 As ? **0.6bh** (8) **Subject to:** 3

g1 ? ? 4 b h (9) g2 ? 180 ? 7.375 As2 ? Asb h (10) Table 1

presents the optimum designs of this problem and the **parameters used,** 3 including several comparisons with prior research on SD-RC [24], GA and

FLC-AHGA [25], CS [26], FA [27]. In this case study, SOS found the same optimum solution identified by FA 3

in 1/10th the time required by FA using 15 organisms.

A 25-bar Transmission Tower Truss 21

Weight Minimization Over last decades, the

25-bar transmission tower spatial truss (shown in Figure 21

2)

is one of the most studied problems in the field of structural engi- neering optimization. 24

The structure is composed of 25 members and categorized

into 8 groups which are: (1) A1, (2) A2–A5, (3) A6–A9, (4) A10–A11, (5) A12– A13, (6) A14–A17, (7) A18–A21 and (8) A22–A25. The 7

members were constructed from materials with a Prayogo, D. et al../

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CED, Vol. 19, No. 1, March 2017, pp. 36–43 Table 1. Results of the 5

Reinforced Concrete Beam Example As (in2) b (in) h (in) g1 g2 fmin (in2) Average Standard deviation No. of evaluations Note: 1 in2 = 6.425 cm2. Amir and Hasegawa [24] SD-RC 7.8 31 7.79 -0.0205 -4.2012 374.2

N.A. N.A. 396 Yun [25]

Gandomi et al. Gandomi et al. Present study 3

GA GA-FL [26] [27] CS FA SOS 7.2 6.16 6.32 6.32 6.32 32 35 34 34 34 8.0451 8.75 8.5 8.5 8.5 -0.0224 0 0 0 0 -2.8779 -3.6173 -0.2241 -0.2241 -0.2241 366.1459 364.8541 359.2080 359.2080 359.2080

N.A. N.A. N.A. 460.706 359.7726 N.A. **N.A. N.A.** 3

80.7387 1.2832 N.A. 100,000 **N.A.** 3

25,000 2,500 mass density of 2767.99 kg/m3 (0.1 lb/in.3) and an Table 3. Optimum Design Comparison for the Discrete 25- elastic modulus (E) of 68.95 MPa (10,000 ksi). All

Bar Spatial Truss Structure members were **subjected to** 7

stress limitations of ±275.8 MPa (40,000 psi) while all nodes were subject Variables (in2) GA [28] HS [29] HPSO [30] SOS to displacement limitations of ± 0.0226 cm (0.35 in).

A1 0. 1 **0.** 1 **0.** 1 **0.** 1 **A2–A5 1.** 7

8 0.3 0.3 0.3 Loads are shown in Table 2. There are two types of A6–A9 2.3 3.4 3.4 3.4 given variables for this problem. The first version A10–A11 0.2 0.1 0.1 0.1 uses discrete variables, while the second version uses A12–A13 0.1 2.1 2.1 2.1 continuous variables.

A14–A17 0.8 1.0 1.0 1.0 A18–A21 1.8 0. 5 **0.5 0.5** 16

Table 2.

Load Case for the 25-bar Spatial Truss Structure 30

A22–A25 3.0 3.4 3.4 3.4 Weight (lbs) 546.01 484.85 484.85 484.85

Nodes Loads Px (kips) Py (kips) Pz (kips) Note: **1** 13

in2 = 6.425 cm2, 1 lb = 4.448 N. 1 1.0 −10.0 −10.0 2 0.0 −10.0 −10.0 Table 4 outlines the performance of the SOS algo- 3 0.5 0.0 0.0 rithm and the other optimization methods reported 6 0.6 0.0 0.0 in the literature for the continuous-problem version. Note: 1 kips = 4.448 kN SOS used 50 organisms and 20,000 structural analyses. The result for the SOS was found after 30 inde- pendent runs. The results for the other algorithms were referenced from Degertekin and Hayalioglu [35]. It is apparent that the design solution obtained by HS [31] is theoretically infeasible because these solutions violate the design constraint stated in [35]. The results produced by the SOS algorithm were competitive with those produced by TLBO [35] and SAHS [34] and superior to those of HPSO [32], and BB-BC [33]. Furthermore, the SOS algorithm deli- vered a better average solution, and lower standard deviation compared to the TLBO algorithm, support- ing that the SOS algorithm is a better optimization Figure 2.

A 25-bar Spatial Truss Structure method than TLBO **in** 7

terms of consistency. For the discrete-problem version,

discrete variables are selected from the set: 7

Site Layout Optimization for Caisson Struc- D = [0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0, 1.1, 1. ture Fabrication 2, 1.3, 1.4, 1.5, 1.6, 1.7, 1.8, 1.9, 2.0, 2.1, 2.2, 2.3, 2.4, 2 .6, 2.8, 3.0, 3.2, 3.4] (in.2). Table 3 summarizes the The performance of SOS was validated for solving

results obtained by the SOS algorithm and the **other** 2

construction site-level facility layout, a function

optimization methods reported **in** the **literature.** within **the** field **of** 13

construction management. Next, a

HPSO obtained a minimum weight of 13

219.92 kg real-life site-level layout problem previously posited (484.85 lbs) in over 25,000 structural analyses. SOS by Kim et al. [36] was investigated. The aim of this algorithm obtained the same in 20,000 structural case study was to design the site layout for caisson analyses with population size of 50. structure fabrication. The site layout considered nine Table 4. Optimum Design Comparison for the Continuous

25-bar Spatial Truss Structure Variables (in2) A1 A2–A5 A6–A9 A10–A11 A12–A13 A14–A17 A18–A21 A22–A25 Weight 12

(lbs) Constraint tolerance (%) Average Weight (lbs) Standard deviation (lbs) No. of structure analyses

Note: 1 in2 = 6. 425 cm2, 1 lb = 4. 448 N. 41

HS [31] 0.047 2.022 2.950 0.010 0.014 0.688 1.657 2.663 544.38 0.206 N/A N/A 15,000 HPSO [32] BB-BC [33] SAHS [34] TLBO [35] SOS 0.010 0.010 0.010 0.0100 0.0100 1.970 2.092 2.074 2.0712 1.9848 3.016 2.964 2.961 2.9570 2.9954 0.010 0.010 0.010 0.0100 0.0100 0.010 0.010 0.010 0.0100 0.0100 0.694 0.689 0.691 0.6891 0.6810 1.681 1.601 1.617 1.6209 1.6784 2.643 2.686 2.674 2.6768 2.6651 545.19 545.38 545.12 545.09 545.180 None None None None None N/A 545.78 545.94 545.51 545.292 N/A 0.491 0.91 0.42 0.102 125,000 20,566 9,051 15,318 20,000 facilities including: (1) steel plate storage, (2) con- summarizes the results obtained by the SOS algo- crete mold storage, (3) steel rod storage, (4) concrete rithm and by the other algorithms over 100 inde- curing place, (5) fabrication factory of caisson wall, pendent runs. The best-known answer for this case (6) prefabrication factory of base plate, (7) steel rod study is [9 1 8 7 6 5 3 2 4] with a total travel distance factory, (8) crane 1, and (9) crane 2. of 7727 meters. SOS algorithm delivered the best These nine predetermined facilities must be average solution, worst solution, and lower standard properly assigned to nine predetermined locations deviation in comparison with DE and PSO. Further- scattered over the site. The goal of this case study is more, SOS achieved the highest success rate in to obtain the optimum layout which has the shortest finding the best solution over 100 runs. total traveling distance between facilities. The total traveling distance (TD) minimization problem is Table 5. Traveling Frequencies between Two Locations stated as: n n n Location 1 2 3 4 5 6 7 8 9 Minimize: ? ? ? δxi x fxi x dij (11) 1 0 5 2 2 1 1 4 1 2 2 5 0 2 5 1 2 7 8 2 i?1 x?1 j?1 3 2 2 0 7 4 12 9 4 5 Subject to: 4 2 5 7 0 20 7 8 1 8 n 5 1 1 4 20 0 30 4 10 3 ? δxi ? 1 , i = 1, 2, 3, …, n (12) x ?1 67 14 27 129 78 304 05 50 87 156 where

n is the number of facility locations; is the 36

8 1 8 4 1 1 8 7 0 9 permutation matrix variable such that when facility 9 2 2 5 8 3 15 6 9 0

x is assigned to location I, is the 40

traveling Table 6. Distance between Two Locations (m) frequency of the construction crew between facilities Location 1 2 3 4 5 6 7 8 9 x and I and is the distance between location i 1 0 15 25 33 40 42 47 55 35 and j. The traveling frequency and distance table are 2 15 0 10 18 25 27 32 42 50 shown in Table 5 and Table 6, respectively. 3 25 10 0 8 15 17 22 32 52 4 33 18 8 0 7 9 14 24 44 In this experiment, we compared SOS with PSO and 5 40 25 15 7 0 2 7 17 37 DE. Because the site-level facility layout is a per- 6 42 27 17 9 2 0 5 15 35 mutation problem, we modified the continuous-based 7 47 32 22 14 7 5 0 10 30 8 55 42 32 24 17 15 10 0 20 initial solution vector into the permutation vector 9 35 50 52 44 37 35 30 20 0 using the indices that would sort the corresponding initial solution vector. The experiment setup was as Table 7. Result of Site-level Facility Layout for Caisson follows: All the algorithms used the same common Structure control parameters with

a population size of 50 and a total of 20,000 function evaluations. 26

The crossover DE PSO SOS

rate (CR) and the scaling factor (F) for DE were 29

Best (m) 7727 7727 7727 Mean (m) 7769.53 7916.55 7734.90 chosen as 0.9 and 0.5, respectively. The cognitive and Worst (m) 8304 8579 7863 social factors (c1 and c2) were set to 1.8 and the Standard deviation (m) 99.42 215.77 23.80 inertia weight (w) was set to 0.6 for PSO. Table 7 Success Rate 74/100 32/100 89/100 Prayogo, D. et al../

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CED, Vol. 19, No. 1, March 2017, pp. 36–43 Conclusion This 5

paper introduced the use of

a new optimization algorithm called Symbiotic Organisms Search (SOS) 2

in civil engineering applications. SOS

is a population based nature-inspired algorithm that mimics the 31

interactive behavior

between organisms in an ecosystem. The three phases of mutualism, commen- salism, and parasitism inspire SOS to find the 10

opti- mal solution for a given objective. Incorporating the characteristic of natural organism interactions into the search strategy supported the superior per- formance

of the SOS algorithm. In this paper, we first validate the performance of SOS against different 25

optimization methods in constrained benchmark problems and then test the performance of SOS in numerous practical civil engineering problems. SOS precisely identified all optimum solutions in every run with significantly fewer function evaluations than algorithms tested in previous works. The novel SOS algorithm presented in this paper is adequately robust to solve various civil engineering problems. The proposed model may be an effective new tool to guide and support the decision-making process of practitioners. References 1. Nahry, Tjahjono, T., and Satiti, Y.J., The Opti- mization Model of Runway and Gate Assign- ment, Civil Engineering Dimension, 15(2), 2013, pp. 129-136. 2. Liao, T.W., Egbelu, P.J., Sarker, B.R., and Leu, S.S., Metaheuristics for Project and Construction Management – A State-of-the-art Review, Auto- mation in Construction, 20(5), 2011, pp. 491-505. 3. Osman, I.H. and Laporte, G., Metaheuristics: A Bibliography, Annals of Operations Research, 63, 1996, pp. 513-623. 4. Holland, J.H., Adaptation in Natural and Arti- ficial Systems, University of Michigan Press, 1975. 5. Kennedy, J. and Eberhart, R., Particle Swarm Optimization, Proceedings of the IEEE Inter- national Conference on Neural Networks, Perth, Australia, 1995, pp. 1942-1948. 6. Storn, R. and Price, K., Differential Evolution - A Simple and Efficient Heuristic for Global Opti- mization over Continuous Spaces, Journal of Global Optimization, 11(4), 1997, pp. 341-359. 7. Karaboga, D. and Basturk, B., A Powerful and Efficient Algorithm for Numerical Function Optimization: Artificial Bee Colony (ABC) Algo- rithm, Journal of Global Optimization, 39(3), 2007, pp. 459-471. 8. Xu, J. and Li, Z., Multi-Objective Dynamic Con- struction Site Layout Planning in Fuzzy Ran- dom Environment, Automation in Construction, 27(0), 2012, pp. 155-169. 9. Yang, I.-T., Using Elitist Particle Swarm Opti- mization to Facilitate Bicriterion Time-Cost Trade-Off Analysis, Journal of Construction Engineering and Management, 133(7), 2007, pp. 498-505. 10. Ponz-Tienda, J.L., Yepes, V., Pellicer, E., and Moreno-Flores, J., The Resource Leveling Pro- blem with Multiple Resources using an Adaptive Genetic Algorithm, Automation in Construction, 29, 2013, pp. 161-172. 11. Cheng, M.-Y., Prayogo, D., Wu, Y.-W., and Lukito, M.M., A Hybrid Harmony Search Algorithm for Discrete Sizing Optimization of Truss Structure, Automation in Construction, 69, 2016, pp. 21-33. 12. Cheng, M.-Y. and Prayogo, D., A Novel Fuzzy Adaptive Teaching–learning-based Optimization (FATLBO) for Solving Structural Optimization Problems, Engineering with Computers, 33(1), 2017, pp. 55-69. 13. Camp, C.V. and Huq, F., CO2 and Cost Optimi- zation of Reinforced Concrete Frames using a Big Bang-big Crunch Algorithm, Engineering Structures, 48, 2013, pp. 363-372. 14. Cheng, Y.M., Li, L., and Fang, S.S., Improved Harmony Search Methods to Replace Variatio- nal Principle in Geotechnical Problems, Journal of Mechanics, 27(01), 2011, pp. 107-119. 15. Cheng, M.Y. and Prayogo, D., Modeling the Permanent Deformation Behavior of Asphalt Mixtures using a Novel Hybrid Computational Intelligence, ISARC 2016 - 33rd International Symposium on Automation and Robotics in Construction, 2016. 16. Cheng, M.-Y., Prayogo, D., and Wu, Y.-W., Novel Genetic Algorithm-based Evolutionary Support Vector Machine for Optimizing High-Perfor- mance Concrete Mixture, Journal of Computing in Civil Engineering, 2013, pp. 06014003. 17. Cheng, M.-Y., Firdausi, P.M., and Prayogo, D., High-performance Concrete Compressive Strength Prediction using Genetic Weighted Pyramid Operation Tree (GWPOT), Engineering Appli- cations of Artificial Intelligence, 29, 2014, pp. 104-113. 18. Cheng, M.-Y. and Prayogo, D., Symbiotic Orga- nisms Search: A New Metaheuristic Optimiza- tion Algorithm, Computers & Structures, 139, 2014, pp. 98-112. 19. Tejani, G.G., Savsani, V.J., and Patel, V.K., Adaptive Symbiotic Organisms Search (SOS) Algorithm for Structural Design Optimization, Journal of Computational Design and Engineer- ing, 2016. 20. Tran, D.-H., Cheng, M.-Y., and Prayogo, D., A Novel Multiple Objective Symbiotic Organisms Search (MOSOS) for Time–cost–labor Utilization Tradeoff Problem, Knowledge-Based Systems, 94, 2016, pp. 132-145. 21. Cheng, M.-Y., Chiu, C.-K., Chiu, Y.-F., Wu, Y.- W., Syu, Z.-L., Prayogo, D., and Lin, C.-H., SOS Optimization Model for Bridge Life Cycle Risk Evaluation and Maintenance Strategies, Journal of the Chinese Institute of Civil and Hydraulic Engineering, 26(4), 2014, pp. 293-308. 22. Panda, A. and Pani, S., A Symbiotic Organisms Search Algorithm with Adaptive Penalty Func- tion to Solve Multi-objective Constrained Opti- mization Problems, Applied Soft Computing, 46, 2016, pp. 344-360. 23. Deb, K., An Efficient Constraint Handling Method for Genetic

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