SAJSET
ISSN: 2992-3581
Savannah Journal of Science and Engineering Technology
Volume: 01; Issue: 05; Pages: 263-268; 2023.
www.sajsetjournal.com.ng
DOI: xx.xxxx.x/sajset-01-2023-0056
SAJSET
ISSN: 2992-3581

Comparative evaluation of hydraulic conductivity of compacted bio-cemented lateritic soil using nature-inspired optimization algorithms

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Paper History
Received: 23rd Aug., 2023
Accepted: 2nd Sept, 2023
Published: Sept, 2023

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Abstract:
Until recently, the use of microorganism to improve the Engineering properties of soil have not received the needed attention of researchers in the related areas. This study evaluates the laboratory results of hydraulic conductivity (k) of compacted Sporosarcina pasteurii (S. pasteurii) treated lateritic soil for landfill application. Specimens prepared using stepped S. pasteurii suspension density of 0, 1.50 x 10^8, 6.0 x 10^8, 1.20 x 10^9, 1.80 x 10^9 and 2.40 x 10^9 cells/ml at -2 % and +4 % moulding water contents (MWCs) relative to optimum moisture content (OMC) and cured for 12 hours at 24 ±2°C before saturation were considered. A modelling software (Gene Expression Programming GeneXpro tools 5.0) was used to formulate the model equation (fitness function). The objective function was targeted for maximum permissible k value of 1.0 x 10^{-9} m/s for landfill. The fitness function with coefficient of determination R^2 value = 98.22 % was then incorporated into Bacterial Foraging Optimization (BFO), Particle Swam Optimization (PSO) and the Smell Agent Optimization (SAO) codes in Matrix laboratory 2016 version to predict the minimum k values. Scanning electron microscopy (SEM) indicated the presence of calcite precipitate and bio-film which reduced k values. A strong correlation exists between the measured and the predicted k values. Results of the 1st to 1000th iteration showed k values lower than the maximum permissible value. The 200th, 500th and 1000th iterations recorded the least k value of 0.00E+00 m/s considered to be the best combinations. The three optimization algorithms considered recorded good outputs in the order PSO > SAO > BFO for the laboratory generated k data. Therefore, it is recommended that compacted lateritic soil - S. pasteurii mixture for all the suspension densities considered be used in landfill and waste containment applications.

Keywords: *Bacterial foraging, Correlation, Hydraulic conductivity, Optimization, Smell Agent*

1. Introduction

Any process or methodology undertaken in making the best or most effective use of a situation or source could be termed as optimization. It involves finding an alternative with the most cost effective or utmost achievable performance under a set of given constraints by maximizing desired variables and minimizing undesired ones in order to attain the needed maximum outcome without regard to cost or expense [1]. Study on optimization in microbial induced calcite precipitation (MICP) processes is essential because it provides optimum conditions for microbial reactions [2]. Effective algorithm optimization considers: (1) An objective function. (2) Constraints and (3) A set of data to test the algorithm.

Three optimization algorithms namely, Bacterial Foraging Optimization Algorithm (BFOA), the Particle Swarm Optimization Algorithm (PSOA) and Smell Agent Optimization Algorithm (SAOA) algorithms were considered in the study.

1.1 Bacterial Foraging Optimization (BFO):

It was first presented by [3] in which the movement behaviour of *Escherichia coli* (*E. coli*) bacteria present in human intestines is mimicked either by an individual bacterium or group of bacteria. Bacterial foraging (i.e., bacterial movement) has been studied by biologists for decades, but there were very few accounts until the 70s [4]. This stimulated the curiosity of numerous investigators [e.g., 1,5-7], that resulted in what is called bacterial foraging patterns. During foraging, there are principally two types of bacterial motility namely, flagellum-dependent and flagellum-independent [8-10]. Biologists have established that microbial movement was not arbitrary and random, but their cells respond by directing their movement toward or away from certain stimuli through the process known as chemotaxis [11]. BFOA is among the family of nature-inspired optimization algorithms which includes Genetic Algorithms (GAs), Evolutionary Programming (EP), Evolutionary Strategies (ES), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO) [12].

1.2 Smell Agent Optimization (SAO):

It is an optimization algorithm developed using the phenomenon of smell perception [13;14]. The concept of SAO is governed by three distinct modes which was derived from perception of smell. The first mode called the sniffing mode in which the agent senses the smell molecules, evaluate to know its exact position and draw a conclusion if to investigate for its source or not. The second mode called the trailing mode in which the agent tracks the smell molecules for the search of the smell source based on the earlier decision from the sniffing mode. The third mode assists the agent to avoid been trapped at local minimum and it is called the random mode [15].

1.3 Particle Swarm Optimization (PSO)

It is the pioneer swarm metaheuristics algorithms inspired by the principles of birds' flocks and school of fish [16]. The process of PSO is initialized by a set of the randomly generated initial population of solutions [17]. Each potential solution is assigned a random velocity with which they are flown into the optimization hyperspace. Each particle keeps a record of its own position coordinates in the hyperspace which is associated with the optimum solution obtained so far. This is called the personal best (pbest). The entire particles in the swarm also keep track of the overall best and its location in the hyperspace. This overall best value is called the global best (gbest) [18]. Assuming an *n*-dimensional search space, the position and velocity of a particle *i* is given [19]. The initial positions are randomly generated and the fitness of each particle in these positions is evaluated and the gbest position is determined. The fitness of the updated position of the particles is evaluated and the updated fitness is determined. This fitness is compared with the previous fitness and the most favourable fitness is kept. The pbest and gbest positions were updated and the entire process of PSO repeats itself until the termination criteria are reached.

2. Methods

2.1 Biofilm formation

Generally, genotypic and phenotypic methods (i.e., Congo Red Agar, CRA and Microtiter Plate, MTP, respectively) are used to confirm the capability of an organism to form biofilm [20]. According to [21], the CRA medium was made using mixtures of 37 g/l BHI broth, 50 g/l sucrose, 10 g/l agar, and 0.8 g/l Congo red. Congo red stain was prepared as a concentrated aqueous solution and then autoclaved at 121^{o} C for 15 min alone from other medium components, and was added after the agar had cooled to a temperature of about 55^{o} C. The plates were inoculated with the organism and incubated at 37^{o} C for 24 hours. After 24 - 48 hours, the plates were checked for any possible change in the colour of the colonies. An organism that can produce biofilm will indicate black colonies, while non-producing organism developed red colonies (i.e., no change in colour of the CRA).

2.2 Optimization algorithm model equations

A modelling software called Gene Expression Programming (GEP) GeneXpro tools 5.0 developed by [22] was used to formulate the model equation. The laboratory hydraulic conductivity (k) data was the objective function as shown in equation (1) with the coefficient of determination, $R^2 = 98.22$ %.

$$\vartheta = \sum_{i=1}^{N}[\alpha + \beta + \delta] \qquad (1)$$

Where

$$\alpha = Tanh(2.09 + Cosx_8) * Sin(-x_9 - 8.21) * Tan^{-1}(x_8 - x_{10}) + Sin(x_4 x_2) * Tan(11.08 - x_{10}) * Tanh(x_{10} \times 5) * (x_2 x_6)$$

$$\beta = Cos\left(e^{(x4x6)} * Tan^{-1}\left(\frac{1}{x_9}\right) - x_3\right)$$

$$\delta = Sin\left(\frac{1}{(x_{10}x_7 + 2.47)x_1} - \frac{x_9}{x_1}\right) - x_9$$

When subjected to such limit expressed in equations (2) and (3), respectively:

$$x_{1\,min} \leq x_1 \leq x_{1\,max} \qquad (2)$$

$$x_{10\,min} \leq x_{10} \leq x_{10\,max} \qquad (3)$$

Where: ϑ is the predicted hydraulic conductivity (the dependent variable) x_1 to x_{10} are the independent variables as defined as: x_1 = Bulk density, x_2 = Void ratio, x_3 = Porosity, x_4 = Moulding water content relative optimum, x_5 = Viscosity of bacterial suspension and cementation reagent, x_6 = Compactive effort, x_7 = Bacterial suspension density, x_8 = Liquid Limit, x_9 = Plasticity Index, and x_{10} = Calcite content.

3. Results and discussion

In any optimization algorithm, the objective function is either for maximization or minimization. In this study, the objective function was targeted towards minimization of the hydraulic conductivity value of the compacted lateritic soil treated with *S. pasteurii* that did not exceed the maximum recommended value of 1.0 x 10^{-9} m/s. A summary of the laboratory measured hydraulic conductivity values with their corresponding independent variables is given in Table 1. The k values were used to develop the objective function (model equation) in equation (1).

The results of the predicted k obtained indicate that the 1st to 1000th iteration recorded k values below the maximum recommended value of 1.0 x 10^{-9} m/s with the corresponding independent variables that constitute the model equation. All the values recorded met the requirement since the algorithm targeted minimization of the objective function. Therefore, the 200th, 500th and 1000th iterations with their corresponding variables that recorded the least hydraulic conductivity values were considered to be the best combinations.

Table 1: Laboratory measured hydraulic conductivity values used to develop the model equation

k	ρb	e	n	$MWRO$	$Visco$	CE	BS	LL	PI	CC
y	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}
-19.32	2.03	0.55	0.36	17.30	10.00	-1.00	0.00	44.00	22.45	2.00
-18.85	2.01	0.59	0.37	17.30	23.00	-1.00	0.50	40.40	19.17	6.80
-19.21	2.06	0.52	0.34	17.30	21.00	-1.00	2.00	38.20	18.08	8.60
-19.39	2.04	0.54	0.35	17.30	26.00	-1.00	4.00	37.80	18.76	11.80
-19.05	2.03	0.57	0.36	17.30	27.00	-1.00	6.00	36.50	18.88	22.00
-19.09	2.01	0.59	0.37	17.30	29.00	-1.00	8.00	38.00	18.78	5.80
-19.51	2.11	0.46	0.31	16.50	10.00	0.00	0.00	44.00	22.45	2.00
-19.71	2.05	0.53	0.35	16.50	23.00	0.00	0.50	40.40	19.17	6.80
-19.53	2.12	0.44	0.30	16.50	21.00	0.00	2.00	38.20	18.08	8.60
-19.31	2.06	0.53	0.35	16.50	26.00	0.00	4.00	37.80	18.76	11.80
-19.57	2.08	0.49	0.33	16.50	27.00	0.00	6.00	36.50	18.88	22.00
-20.39	2.06	0.48	0.32	16.50	29.00	0.00	8.00	38.00	18.78	5.80
-20.04	2.19	0.35	0.26	15.80	10.00	1.00	0.00	44.00	22.45	2.00
-20.77	2.09	0.48	0.32	15.80	23.00	1.00	0.50	40.40	19.17	6.80
-20.82	2.08	0.49	0.33	15.80	21.00	1.00	2.00	38.20	18.08	8.60
-21.56	2.13	0.42	0.30	15.80	26.00	1.00	4.00	37.80	18.76	11.80
-21.32	2.13	0.43	0.30	15.80	27.00	1.00	6.00	36.50	18.88	22.00
-20.39	2.18	0.37	0.27	15.80	29.00	1.00	8.00	38.00	18.78	5.80

3.1 Optimization algorithms

Optimization algorithms comparison on the hydraulic conductivity of compacted lateritic soil treated with *S. pasteurii.* The variation of the optimized k values with iterations for BFO, PSO and SAO algorithms are shown in Figure 1. This was done to demonstrate the law of "no free lunch theorem" which states that ''in computational complexity and optimization there is no recognized single nature inspired optimization technique capable of resolving all optimization problems. However, all the optimization algorithms worked in this order of ranking PSO > SAO > BFO for the generated data as shown in Figure 1. Furthermore, the variation of the optimized hydraulic conductivity for the algorithms with bacterial population shown in Figure 2 demonstrated that all the algorithms recorded a good output in the order recorded in Figure 1.

3.2 Biofilm formation

The phenotypic expression test on the ability of *S. pasteurii* to form bio-film is shown on Plate I. Plate IIa shows the Congo Red Agar before the streaking of *S. pasteurii*, Plate I b shows the results from *S. pasteurii,* while Plate I c shows results from the lateritic soil. A positive result from the pure culture and the lateritic soil was observed in addition to bio-film formation. Additional bio-chemical reactions / growth pattern by other microbial strains were also observed, which suggest that other microbial strains may have contributed in the bio-film formation (see Plate I b and c). Similar findings were reported by [23].

The micrographs of specimens of the natural lateritic soil and microbial induced calcite precipitate treated soil subjected to scanning electron microscopy (SEM) are shown on Plate II. In MICP technique for soil improvement, bio-clogging has been reported to be responsible for the reduction in hydraulic conductivity [24;25]. It can be observed that there are voids existing in the micrograph for the natural soil see Plate IIa) which were partially filled by calcite precipitate when treated with *S. pasteurii* suspension density of 1.20 x 10^9 cells/ml through bio-clogging (see Plate IIb). Plate IIc shows The micrograph of lateritic soil treated with *S. pasteurii* suspension density of 2.40 x 10^9 cells/ml, which is the highest considered in this study, depicts a spongy appearance that suggests the formation of bio-film that has been reported to reduce k values [26;27. It can therefore be inferred that the decrease in k values of the treated specimens when compared with the natural specimens could be mainly due to the precipitation of calcite through bio-clogging and bio-film formation.

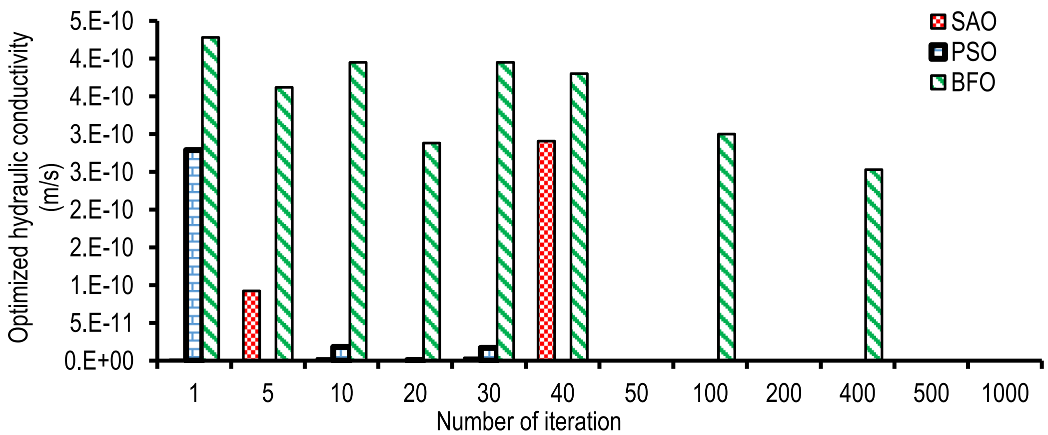

Figure 1. Variation of optimized hydraulic conductivity values with iteration

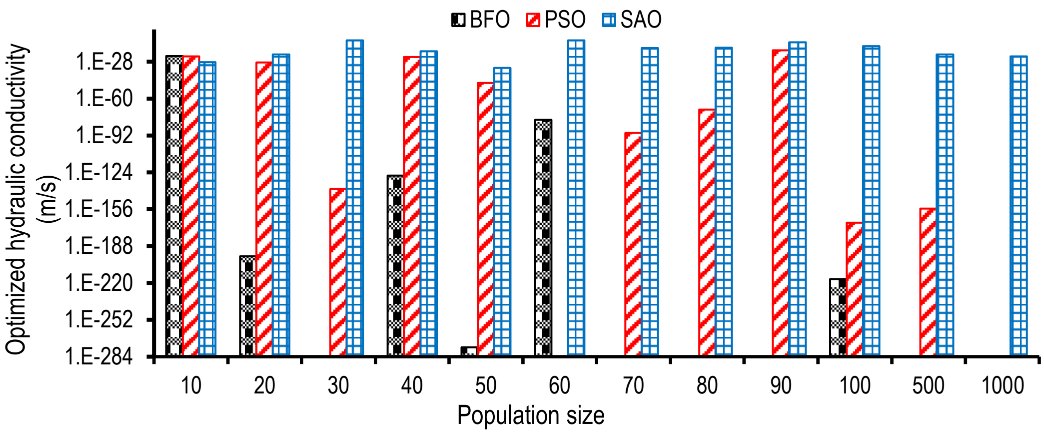

Figure 2. Variation of optimized hydraulic conductivity values with population size

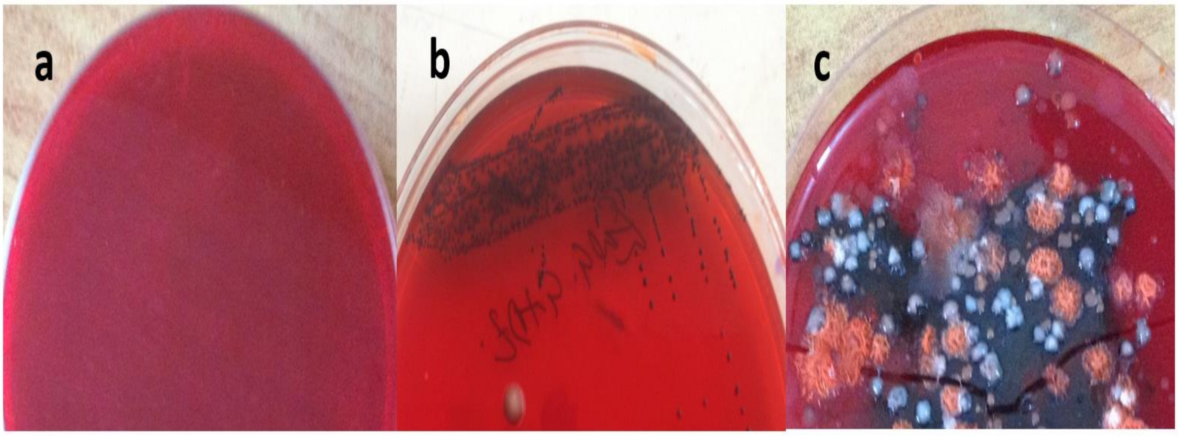

Plate I: Phenotypic bio-film expression test: (a) Congo Red Agar before streaking (b) pure bacterial culture (c) Lateritic soil

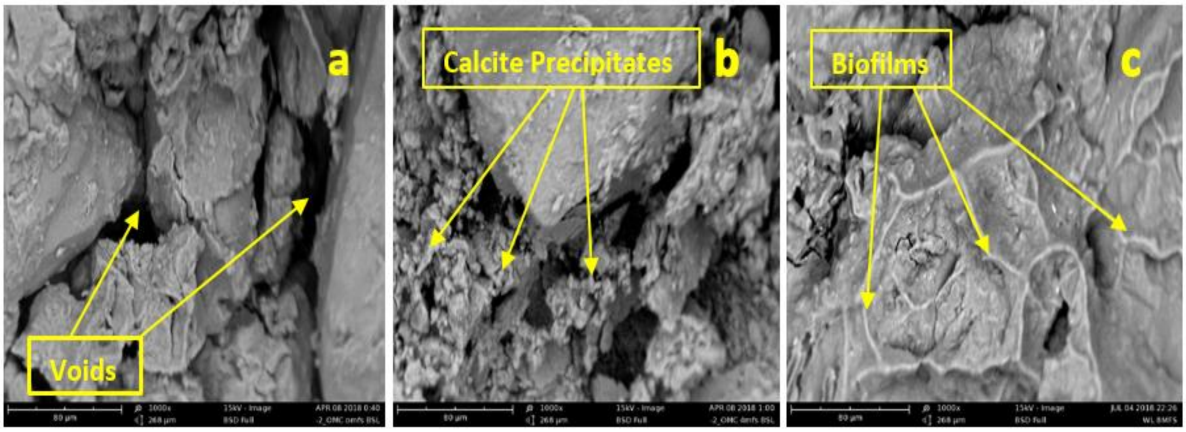

Plate II: Micorgraphs of hydraulic conductivity specimens at x1000 magnification: (a) Natural lateritic soil (b) Lateritic soil treated with *Sporosarcina pasteurii* suspension density of 1.20 x 10^9 cells/ml (c) Lateritic soil treated with *Sporosarcina pasteurii* suspension density of 2.40 x 10^9 cells/ml

4. Conclusion

Based on the results of the study carried out, the three optimization algorithms (i.e., Bacterial Foraging, Particle Swarm and Smell Agent) employed in the optimization of the laboratory generated hydraulic conductivity (k) data of compacted lateritic soil treated with *S. pasteurii,* worked well in the ranking Particle Swarm Optimization (PSO) > Smell Agent Optimization (SAO) > Bacterial Foraging Optimization (BFO). The decrease in the laboratory measured k values of the treated specimens was principally due to the precipitation of calcite which facilitated bio-clogging of voids in the soil and bio-film formation on soil particles when compared with the natural specimens.

Acknowledgements

The authors wish to acknowledge the assistance of Abiodun P. Adegoke and late Sani Mohammed of the Department of Microbiology, Modibbo Adama University,

Yola for the isolation of the micro-organisms used in this study.

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