An Adaptive Tunicate Swarm Algorithm for Optimization of Shallow Foundation

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ABSTRACT This paper aims to introduce an adaptive metaheuristic algorithm based on tunicate swarm optimization (TSA) for effectively solving global optimization problems and the optimum design of a shallow spread foundation. The proposed adaptive tunicate swarm optimization (ATSA) has two main phases at each iteration: searching all around the search space based on a randomly selected tunicate and improving the search using the position of the best tunicate. This modification improves the algorithm's exploration ability while also preventing premature convergence. The suggested algorithm's performance is confirmed using a set of 23 mathematical test functions of well-known CEC 2017 and the outcomes are compared with TSA as well as some effective optimization algorithms. In addition, the new method automates the optimum design of shallow spread foundations while taking two objectives into account: cost and CO_2 emissions. The analysis and design procedures are based on both geotechnical and structural limit states. A case study of a spread foundation has been solved using the proposed methodology, and a sensitivity analysis has been conducted to investigate the effect of soil parameters on the total cost and embedded CO_2 emissions of the foundation. The simulation results demonstrate that, when compared to other competing algorithms, ATSA is superior and may produce better optimal solutions.

INDEX TERMS Tunicate swarm, metaheuristic, shallow foundation, cost, CO_2 emissions.

I. INTRODUCTION

Many real-world design problems can be considered optimization problems, and an appropriate optimization method is required for the solution. On the other hand, design problems have become more complicated when discontinuities, incomplete information, dynamicity, and uncertainties are involved. In such a case, classical optimization algorithms based on mathematical principles demand exponential time or may not find the optimal solution at all. To overcome the mentioned problem, during the last few decades, introducing new efficient metaheuristic optimization algorithms to deal with the drawbacks of classical techniques has been of great concern. The privileges of these algorithms include derivation-free mechanisms, simple concepts and structure, local optima avoidance, and effectiveness for discrete and

The associate editor coordinating the review of this manuscript and approving it for publication was Bilal Alatas.

continuous functions. Accordingly, there is an increasing interest in presenting new metaheuristic algorithms that offer higher accuracy and efficiency in dealing with complex optimization problems.

Particle swarm optimization was proposed by Kennedy and Eberhart [1], ant colony optimization was introduced by Dorigo and Di Caro [2], harmony search was proposed by Geem *et al.* [3], firefly algorithm was suggested by Yang [4], gravitational search algorithm was introduced by Rashedi *et al.* [5], sine cosine algorithm was developed by Mirjalili [6], crow search algorithm was proposed by Askarzadeh [7], spotted hyena optimizer was introduced by Dhiman and Kumar [8], Harris hawks optimization was presented by Heidari *et al.* [9], emperor penguin optimizer was proposed by Dhiman and Kumar [10], chameleon swarm algorithm was developed by Braik [11], sooty tern optimization algorithm was proposed by Dhiman and Kuar [12], hunter–prey optimization was developed by

Naruei *et al.* [13], and rat swarm optimizer was introduced by Dhiman *et al.* [14].

Although metaheuristic methods can yield acceptable results, no algorithm can solve all optimization problems better than others. In addition, in most engineering optimization problems, the objective function is discontinuous and has a large number of design variables. As a result, several research projects have been carried out to enhance the original metaheuristic algorithms' performance and efficiency and apply them to engineering problems. Dhiman [15] introduced a hybrid bio-inspired metaheuristic optimization approach, namely the Emperor Penguin and Salp Swarm Algorithms for engineering problems. Eslami *et al.* [16] proposed improved particle swarm optimization with chaotic sequence for optimal location of the power system stabilizer. Bingol and Alatas [17] proposed chaotic league championship algorithms for complex benchmark functions. Kaveh *et al.* [18] applied a non-dominated sorting genetic algorithm to solve the performance-based multi-objective optimal design of steel moment-frame structures considering the initial cost and the seismic damage cost. Dhiman *et al.* [19] developed a novel binary emperor penguin optimizer for automatic feature selection. Li and Wu [20] proposed an improved slap swarm optimization for determining the crucial failure surface in slope stability evaluation. Temur [21] introduced a hybrid version of teaching learning-based optimization for the optimum design of cantilever retaining walls under seismic loads. Bardhan *et al.* [22] proposed a modified equilibrium optimizer for predicting soil compression index. For pile group foundation design, Chan *et al.* [23] used an automated optimal design method based on a hybrid genetic algorithm. Bingol and Alatas [24] proposed enhanced optics inspired optimization for real-world engineering problems. Kumar and Dhiman [25] presented a comparative study of fuzzy optimization through fuzzy number. Khajehzadeh *et al.* [26] proposed modified gravitational search algorithm for multi-objective optimization of foundation.

Shallow spread foundation, a geotechnical structure that transfers loads to the soil beneath it immediately and is one of the most significant and sensitive structural components, has received a lot of attention in recent studies. Structures' functionality can be jeopardized unless the effective loads are successfully sent to the earth by a well-designed foundation. As a result, the proper design of the spread foundation has received wide attention in recent investigations. Traditionally, in the design of spread foundations, initial assumed dimensions will be checked for all geotechnical and structural limit states. If the dimensions are unable to satisfy the limitations, they will be changed until all of the requirements are met. The construction cost is not taken into account throughout this time-consuming iterative procedure. In the optimum design of these structures, the dimensions that provide the minimum cost or weight and satisfy all the requirements are defined automatically. Actually, spread foundations are widely used and typically involve a large amount of material volume. In addition, a considerable portion of the structure's cost is associated with the foundations, and the economical design of foundations is an essential concern for geotechnical engineers. Therefore, several optimum design approaches for spread foundations have already been developed, with the main goal of these studies being cost reduction. Wang and Kulhawy [27] devised a design technique that took construction economics into account directly, resulting in a foundation with the lowest possible construction cost. Nigdeli *et al.* [28] employed three metaheuristic optimization algorithms, including Flower Pollination Algorithm, Harmony Search and Teaching-Learning Based Optimization algorithm for the optimum design of reinforced concrete footings. Gandomi and Kashani [29] considered the final cost of foundation as an objective function and applied eight swarm intelligence techniques to the problem. Kashani *et al.* [30] investigated the performance of three evolutionary algorithms, namely, evolution strategy, differential algorithm, and biogeography-based optimization algorithm for foundation design optimization.

On the other hand, as the annual emissions of carbon dioxide (CO_2) have grown by up to 80% since 1970, the consideration of CO_2 emissions in the design of concrete structures has become of greater interest among researchers. The main binder used in concrete is Portland cement, and a large amount of CO_2 is produced during its manufacturing. Therefore, minimization of embedded CO_2 emissions seems crucial to incorporate into the design criteria of reinforced concrete structures. For optimization of embedded carbon dioxide (CO_2) emissions and the economic cost of reinforced concrete walls, Yepes *et al.* [31] suggested a hybrid optimization method based on a variable neighborhood search threshold acceptance strategy. Paya-Zaforteza *et al.* [32] implemented the well-known simulated annealing (SA) algorithm to design reinforced concrete (RC) building frames with the lowest possible embedded CO_2 emissions and the lowest possible RC frame construction cost. Using a hybrid glowworm swarm optimization algorithm, Yepes *et al.* [33] developed a way for optimizing cost and CO_2 emissions while designing precast–prestressed concrete road bridges with a double U-shape cross-section. Khajehzadeh *et al.* [34] developed an effective hybrid evolutionary approach based on an adaptive gravitational search algorithm for multi-objective optimization of reinforced concrete (RC) retaining walls.

Recently, Kaur *et al.* [35] suggested the tunicate swarm algorithm (TSA) as a new bioinspired meta-heuristic optimization technique. Tunicates use swarm intelligence and jet propulsion at sea to choose the optimal state for seeking food in their surroundings. TSA outperforms other competitor approaches when it comes to identifying optimal solutions and is well-suited to real-world optimization challenges. Sharma *et al.* [36] applied TSA for parameter extraction of the photovoltaic module. Li *et al.* [37] developed an improved version of the tunicate swarm algorithm (ITSA) for solving and optimizing the dynamic economic emission dispatch (DEED) problem. Fetouh and Elsayed [38] proposed an improved tunicate swarm algorithm for optimal control

and operation of fully automated distribution networks. Rizk-Allah *et al.* [39] applied an enhanced TSA for solving large-scale nonlinear optimization problems. Al-Wesabi *et al.* [40] developed a multi-objective quantum tunicate swarm optimization with a deep learning model for intelligent dystrophinopathy diagnosis. Mansoor *et al.* [41] proposed an intelligent tunicate swarm algorithm for multiple configurations of Photovoltaic systems under partial shading conditions. Khajehzadeh *et al.* [42] developed a hybrid version of TSA for seismic analysis of earth slopes. Houssein *et al.* [43] presented an improved tunicate swarm algorithm for global optimization and image segmentation.

However, it is prone to becoming stuck in local optima and is unable to find the optimal answer in some difficult circumstances [44].

In order to overcome this weakness, in the current study, an adaptive version of the tunicate swarm algorithm (ATSA) is developed and utilized for spread foundation optimization. Therefore, the main contribution of this work can be summarized as follows:

1- An effective global optimization algorithm (ATSA) based on the tunicate swarm algorithm has been developed.

2- Two separate phases are introduced in the TSA to increase both the global and local search capability of the original algorithm.

3- The performance of ATSA is evaluated on 23 frequently used benchmark functions and compared to other optimization algorithms.

4- To verify the effectiveness of the proposed method for the solution of real-world problems, the new method is applied to spread foundation optimization.

5- In the optimum design of the foundation, total construction cost as well as total CO_2 emissions are considered as objective functions.

II. FOUNDATION OPTIMIZATION

Reinforced spread foundation, as a key geotechnical construction, must securely and reliably support the superstructure, maintain stability against excessive settlement and failure of the soil's bearing capacity, and restrict concrete stresses. Aside from these design goals, spread foundations must meet a number of requirements. In both long and short dimensions, they must have sufficient shear and moment capacities, and the steel reinforcement design must comply with all design codes.

Mathematically, general form of a constraint optimization problem can be expressed as follows:

$$minimize \, f(X)$$
$$subject \, to \, g_i(X) \leq 0, \quad i = 1, 2, \ldots, p, \quad (1)$$
$$h_j(X) = 0, \quad j = 1, 2, \ldots, m,$$
$$X^L \leq X \leq X^U \quad (1)$$

where X is n dimensional vector of design variables, $f(X)$ is the objective function, $g(X)$ and $h(X)$, respectively, are inequality and equality constraints. Boundary constraints,

X^L and X^U, are two n-dimensional vectors containing the design variables' lower and upper bounds, respectively.

In the problem of foundation optimization, it is required to identify the objective function, design constraint, and design variables that are presented in the following sub-sections.

A. OBJECTIVE FUNCTION

In the current study, the problem of spread foundation optimization considers the embedded CO_2 emission and the construction cost of the structure. Hence, this optimization problem aims to minimize one of these two objective functions. Both objective functions consider the amount of excavation, formwork, reinforcing steel, concrete, and compacted backfill.

The total cost of the structure is presented in the following equation:

$$f_{cost} = C_s W_{st} + C_c V_c + C_e V_e + C_f A_f + C_b V_b \quad (2)$$

where, W_{st} is the weight of the steel bars, V_c, V_e and V_b denote the volume of concrete, excavation and backfill. A_f shows the area of formwork. C_c, C_e, C_b, C_f and C_s are the unit costs of concrete, excavation, backfill, formwork, and reinforcement, respectively. The unit prices are presented in Table 1 [45].

The next objective which quantify the total amount of CO_2-emissions of the footing can be expressed in the following form:

$$f_{co2} = E_s W_{st} + E_c V_c + E_e V_e + E_f A_f + E_b V_b \quad (3)$$

where, E_c, E_e, E_b, E_f and E_s are the unit emission of concrete, excavation, backfill, formwork, and reinforcement, respectively as presented in Table 1 [45].

TABLE 1. Unit cost and CO2 emission of foundation construction [45].

Item	Unit	Symbol	Value
Cost of earth removal	\$/m³	C_e	25.16
Cost of foundation formwork	\$/m²	C_f	51.97
Cost of reinforcement	\$/kg	C_s	2.16
Cost of concrete	\$/m³	C_c	173.96
Cost of compacted backfill	\$/m³	C_b	3.97
CO₂ emission for earth removal	kg/m³	E_e	13.16
CO₂ emission for foundation formwork	kg/m²	E_f	14.55
CO₂ emission for reinforcement	kg/kg	E_s	3.02
CO₂ emission for concrete	kg/m³	E_c	224.65
CO₂ emission for compacted backfill	kg/m³	E_e	27.20

B. DESIGN VARIABLES

The design factors for the spread footing model are shown in Figure 1. There are two types of design variables: those that define geometrical parameters and those that describe reinforcing steel. The dimensions of the foundation are represented by four geometric design variables, as illustrated in
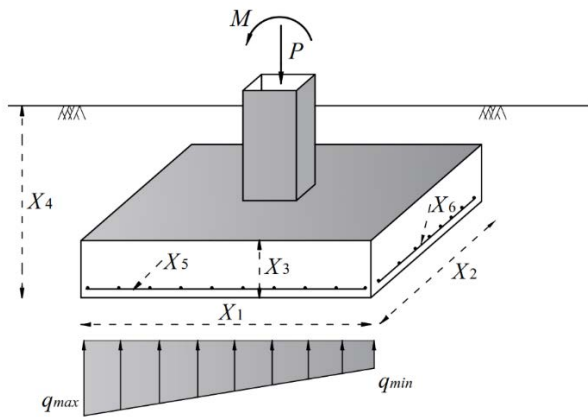
FIGURE 1. Design variables of the footing.

Figure 1. X_1 is the foundation's length, X_2 is the foundation's width, X_3 is foundation's thickness and X_4 is depth of embedment. Moreover, the steel reinforcement has two design variables: X_5 is the longitudinal reinforcement and X_6 is the transverse reinforcement.

C. DESIGN CONSTRAINTS

The forces operating on the footing are depicted in Figure 1. M and P denote the axial load and moment imparted to the footing in this figure. The minimum and maximum bearing pressures on the foundation's base are q_{min} and q_{max}, respectively. The next sub-sections go over the design restrictions that must be taken into account when optimizing the spread footing.

1) BEARING CAPACITY

The foundation's bearing capacity must be sufficient to withstand the forces acting along the base. The maximum stress should be less than the soil's bearing capacity to ensure a safe design:

$$q_{max} \leq \frac{q_{ult}}{FS} \tag{4}$$

where q_{ult} denotes the foundation's ultimate bearing capacity and q_{max} is the maximum contact pressure at the boundary between the foundation's bottom and the underlying soil. The lowest and highest applied bearing pressures on the foundation's base are calculated as follows:

$$q_{\substack{min \\ max}} = \frac{P}{X_1 X_2} \left(1 \mp \frac{6\,e}{X_1} \right) \tag{5}$$

where e denotes the eccentricity, which is defined as the ratio of the overturning moments (M) to the total vertical forces (P).

2) ECCENTRICITY

The following requirements must be met such that tensile forces at the bottom of the footing are avoided:

$$e \leq \frac{X_1}{6} \tag{6}$$

3) SETTLEMENT

According to the following inequalities, foundation settlement should be kept within a legal range:

$$\delta \leq \delta_{all} \tag{7}$$

where δ_{all} is the permitted settlement and δ is the foundation's immediate settlement. The settlement can be estimated as follows using the elastic solution proposed by Poulos and Davis [46]:

$$\delta = \frac{P(1 - \nu^2)}{\kappa_z E \sqrt{X_1 X_2}} \tag{8}$$

where κ_z is the shape factor, ν is the Poisson's ratio and E is modulus of elasticity. In this research, the shape factor proposed by Wang and Kulhawy [27] is used as follows:

$$\kappa_z = -0.0017(X_2/X_1)^2 + 0.0597(X_2/X_1) + 0.9843 \tag{9}$$

where, X_1 is the foundation's length, and X_2 is the foundation's width.

4) ONE-WAY SHEAR

The footing must be viewed as a wide beam for one-way shear. According to ACI [47], the shear strength of concrete measured along a vertical plane extending the whole width of the base and located at a distance equal to the effective depth of the footing (V_u) should be less than nominal shear strength of concrete:

$$V_u \leq \frac{1}{6} \phi_V \sqrt{f_c'} bd \tag{10}$$

where ϕ_V is the shear strength reduction factor of 0.75 [47], f_c is the concrete compression strength, b is the section width, and d denotes the depth at which steel reinforcement is placed.

5) TWO-WAY SHEAR

The tendency of the column to punch through the footing slab is called "punching shear". According to (11), the maximum shearing force in the upward direction (V_u) should be less than the nominal punching shear strength to avoid such a failure.

$$V_u \leq min \left\{ \frac{1 + \frac{2}{\beta_c}}{6}, \frac{\frac{\alpha_s d}{b_0} + 2}{12}, \frac{1}{3} \right\} \emptyset_V \sqrt{f'_c} b_0 d \tag{11}$$

where b_0 is the crucial section's perimeter taken at $d/2$ from the column's face, d denotes the depth at which steel reinforcement is placed, β_c is the ratio of a column section's long side to its short side and α_s is equal to 40 for interior columns.

6) BENDING MOMENT

The nominal flexural strength of the reinforced concrete foundation section should be less than the moment capacity [47]:

$$M_u \leq \phi_M A_S f_y \left(d - \frac{a}{2} \right) \tag{12}$$

where M_u denotes the bending moment of the reaction stresses due to the applied load at the column's face, φ_M presents the flexure strength reduction factor equal to 0.9 [47], A_s denotes the area of steel reinforcement and f_y is the yield strength of steel.

7) REINFORCEMENTS LIMITATION

In each direction of the footing, the amount of steel reinforcement must fulfill minimum and maximum reinforcement area limitations according to the following inequality [47]:

$$\rho_{\min} bd \leq A_S \leq \rho_{\max} bd \tag{13}$$

where A_S is the cross section of steel reinforcement, ρ_{min} and ρ_{max} are the minimum and maximum reinforcement ratios based on the following equations [47]:

$$\rho_{\min} = \max \left\{ \frac{1.4}{f_y}, 0.25 \frac{\sqrt{f'_c}}{f_y} \right\} \tag{14}$$

$$\rho_{\max} = 0.85 \beta_1 \frac{f'_c}{f_y} \left(\frac{600}{600 + f_y} \right) \tag{15}$$

where, β_1 is a constant equal to 0.85 [47].

8) LIMITATION OF EMBEDMENT'S DEPTH

The depth of embedment (X_4) should be limited between 0.5 and 2. Therefore:

$$0.5 \leq X_4 \leq 2 \tag{16}$$

To address the above mentioned limitations and transform a constrained optimization to an unconstrained one, a penalty function method is used in this paper. according to:

$$F(X) = f(X) + r \sum_{i=1}^{p} \max\{0, g_i(X)\}^l \tag{17}$$

where $F(X)$ is the penalized objective function, $f(X)$ is the problem's original objective function presented in (2) and (3) and r is a penalty factor and p in the total number of constraints.

III. TUNICATE SWARM ALGORITHM (TSA)

TSA is a simple meta-heuristic optimizer inspired by the performance of marine tunicates and their jet propulsion systems during navigation and foraging. [35]. This animal has a millimeter-scale form. Tunicate can locate food sources in the sea. In the supplied search space, however, there is no indication of the food source. A tunicate must satisfy three basic conditions when traveling with jet propulsion: it must avoid colliding with other tunicates in the search space; it must take the correct path to the optimal search location; and it must be as close to the best search agent as possible. The candidate solutions (i.e., tunicates) in TSA are looking for the best food source (i.e., the best value of the objective function). The tunicates change their positions in reference to the best tunicates that are stored and improved in each iteration during this process. The TSA starts with a population of randomly generated tunicates based on the design variables' allowable boundaries, as shown in the equation below:

$$\vec{T}_p = \vec{T}_p^{min} + rand \times \left(\vec{T}_p^{max} - \vec{T}_p^{min} \right) \tag{18}$$

where, $\vec{T}_p$ is the position of each tunicate and *rand* is a random number within range [0, 1]. $\vec{T}_p^{min}$ and $\vec{T}_p^{max}$ are design variables' lower and upper bounds, respectively. The tunicates adjust their location during the iterations by the following formula [35]:

$$\vec{T}_p (\vec{x} + 1) = \frac{\vec{T}_p (x) + \vec{T}_p (\vec{x})}{2 + c_1} \tag{19}$$

where, c_1 is a random number within range [0,1] and $\vec{T}_p (x)$ refers to the updated position of the tunicate with respect to the position of the food source based on (20).

$$\vec{T}_p (x) = \begin{cases} SF + A \times \left| SF - rand \times \vec{T}_p \right|, & if \ rand \geq 0.5 \\ SF - A \times \left| SF - rand \times \vec{T}_p \right|, & if \ rand < 0.5 \end{cases} \tag{20}$$

where SF is the food source, which is represented by the population's optimal tunicate position; and A denotes a randomized vector to prevent tunicates from colliding with one another which is modelled as:

$$A = \frac{c_2 + c_3 - 2c_1}{VT_{min} + c_1 (VT_{max} - VT_{min})} \tag{21}$$

where, c_1, c_2 and c_3 are random numbers within range [0, 1]; VT_{min} and VT_{max} reflect the minimum and maximum speeds that are used to create social interaction which considered as 1 and 4, respectively [35].

The TSA algorithm's steps are presented below:

Step 1: Initialize the tunicate population $\vec{T}_p$ based on (18).

Step 2: Choose the initial parameters and maximum number of iterations.

Step 3: Calculate the fitness value of each search agent.

Step 4: The best tunicate is explored in the given search space.

Step 5: Update the position of each tunicate using (19).

Step 6: Adjust the updated tunicate which goes beyond the boundary in a given search space.

Step 7: Compute the updated tunicate fitness value. If there is a better solution than the previous optimal solution, then update the best.

Step 8: If the stopping criterion is satisfied, then the algorithm stops. Otherwise, repeat the Steps 5–8.

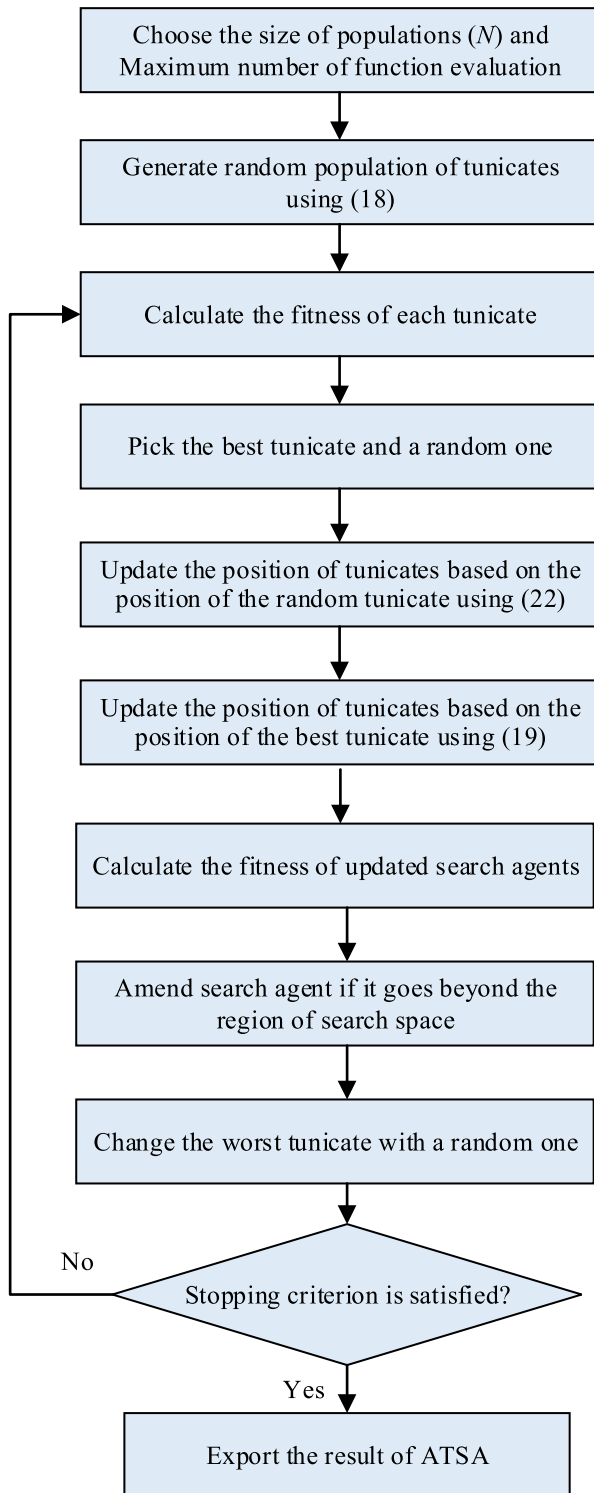*Step* 9: Return the best optimal solution which is obtained so far.

FIGURE 2. Flowchart of the ATSA.

IV. ADAPTIVE TUNICATE SWARM ALGORITHM

Despite the TSA's ability to produce efficient results when compared to other well-known algorithms, it is susceptible to becoming trapped in local optima and is not ideal for very complex problems with several local optima [44]. As shown

in (19) and (20), in TSA, every tunicate updates its position based on the position of the food source (i.e., the position of the best tunicate in the whole population). However, without any knowledge of the position of the food source (FS), there will not be any recovery for the algorithm if premature convergence happens. In other words, once the algorithm has converged, it loses its potential to explore and becomes inactive. Therefore, the TSA algorithm becomes locked at local minimum points as a result of this mechanism. In light of these conditions, an adaptive version of the TSA (ATSA) is proposed to overcome the mentioned weaknesses and increase the search capability and flexibility of the algorithm.

An effective metaheuristic algorithm needs to divide the search process into two phases: exploration and exploitation. Exploration involves exploring new positions far from the current position in the entire search area. The exploration phase takes place when a metaheuristic algorithm attempts to identify the entire solution space and explore the promising areas. In contrast, exploitation refers to the capability of an optimization algorithm to search around near-optimal solutions. This phase allows the optimizer to concentrate on the neighborhood that consists of higher-quality solutions within the searching space. As mentioned earlier, at each iteration pass, the TSA algorithm updates the position of candidate solutions around a single point that is the best solution in the whole population. It means the TSA has a good exploitation capability. However, its weakness is the lack of an effective global search and the algorithm suffers from an effective exploration ability.

In order to improve the performance and exploration capability of the algorithm, the proposed ATSA has two main phases in each iteration. In the first phase (exploration phase), a candidate solution is picked at random instead of the best solution, and the position of the candidate solutions will be updated according to the position of this random tunicate. In addition, to have effective exploration, an optimizer should use its randomized operators to thoroughly explore diverse areas of the search space [9]. Therefore, in the proposed ATSA, two separate random numbers are considered in the tunicate's updating equation to produce solutions in various regions of the search space.

The exploration phase of the ATSA is mathematically modeled as follows:

$$\vec{T}_p(\vec{x}+1) = \vec{T}_p(r) - rand_1 \times |\vec{T}_p(r) - 2 \times rand_2 \times \vec{T}_p(\vec{x})| \tag{22}$$

where $\vec{T}_p(r)$ is randomly selected tunicate form the current population. $rand_1$ and $rand_2$ are random numbers between 0 and 1. This procedure promotes exploration and also allows the TSA algorithm to perform a more robust global search throughout the whole search space.

In the second phase of the ATSA algorithm (exploitation phase), the tunicates update their positions according to the position of the best tunicate found so far, based on (19).

TABLE 2. Description of unimodal benchmark functions.

Function	Name [48]	Range	f_{min}	n (Dim)
$F_1(X) = \sum_{i=1}^{n} x_i^2$	Sphere function	$[-100, 100]^n$	0	30
$F_2(X) = \sum_{i=1}^{n} \|x_i\| + \prod_{i=1}^{n} \|x_i\|$	Schwefel's problem 2.22	$[-10, 10]^n$	0	30
$F_3(X) = \sum_{i=1}^{n} \left(\sum_{j=1}^{i} x_j \right)^2$	Schwefel's problem 1.2	$[-100, 100]^n$	0	30
$F_4(X) = \max_i \{ \|x_i\|, 1 \leq i \leq n \}$	Schwefel's problem 2.21	$[-100, 100]^n$	0	30
$F_5(X) = \sum_{i=1}^{n-1} \left[100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2 \right]$	Generalized Rosenbrock's function	$[-30, 30]^n$	0	30
$F_6(X) = \sum_{i=1}^{n} ([x_i + 0.5])^2$	Step function	$[-100, 100]^n$	0	30
$F_7(X) = \sum_{i=1}^{n} i x_i^4 + random[0,1)$	Quartic function with noise	$[-1.28, 1.28]^n$	0	30

Furthermore, in the proposed ATSA, the worst tunicate with the highest objective function value will be replaced with a randomly generated tunicate at each iteration. Figure 2 shows the flowchart of the proposed ATSA algorithm.

A. COMPARATIVE TIME COMPLEXITY ANALYSIS
In order to evaluate the overall performance of a new optimization algorithm from different points of view, the computational time complexity analysis can be conducted. In computer sciences, the "Big O notation" is a mathematical notation which represents the required running time of an algorithm by considering the growth rate in dealing with different inputs.

The time complexity analysis of most algorithms involves analyses of three components. Likewise, the time complexity analysis of the proposed ATSA also requires analyses of these three components:

1. Time complexity of initialization of the population, generally calculated by O($N \times D$) where N denotes the population size and D denotes the dimensions of the problem.

2. Time complexity of initial fitness evaluation, generally evaluated by O ($N \times F(X)$), where $F(X)$ represents the objective function.

3. Time complexity of the main loop, generally calculated by O ($Maxiterations \times (N \times D + N \times F(X))$), where $Maxiterations$ is the maximum number of iterations.

Hence, the total time complexity of ATSA algorithm is O($Maxiterations (N \times D + N \times F(X))$).

V. PERFORMANCE EVALUATION OF THE ATSA
The effectiveness of the suggested ATSA approach will be investigated in this section. To this aim, on a set of benchmark test functions from the literature, the performance of the new method is compared to that of the standard version of the algorithm (TSA) as well as some well-known

metaheuristic algorithms. These are all minimization problems that can be used to test the new optimization algorithms' robustness and exploration efficiency. The mathematical description and characteristics of these test functions are shown in Tables 2, 3, 4. This benchmark set covers three main groups: unimodal functions with a unique global best for testing the convergence speed and exploitation ability of the algorithms; multimodal functions with multiple local solutions and a global optimum for testing local optima avoidance and exploration capability of an algorithm; and finally multimodal functions with a fixed dimension.

The ATSA algorithm's performance is compared with the original TSA and some efficient optimization methods, including Gravitational Search Algorithm (GSA), Grey Wolf Optimizer (GWO), and Sine Cosine Algorithm (SCA). It's worth noting that the ATSA algorithm evaluates the objective function twice per iteration, whereas the TSA and other approaches do so just once. Therefore, according to the suggestion of the previous studies [35] and to have a fair comparison between the results, the size of the population (N) is considered equal to 40 for ATSA and equal to 80 for TSA and other approaches. In addition, for all techniques, the maximum number of iterations is considered equal to 1000. In this way, in all experiments, the same number of function evaluations, equal to 80,000, is used. The results of a single run may be incorrect since metaheuristic approaches are stochastic. As a result, to generate a meaningful comparison and evaluate the effectiveness of the algorithms, a statistical analysis should be utilized. To address this issue, 30 independent runs for the stated algorithms are performed, with the results presented in Tables 5, 6, 7.

The results of Tables 5, 6, 7, show the best (minimum), worst (maximum), mean (average), median and standard deviation (Std) of the solutions obtained from experiments using the selected optimization algorithms. The best results

TABLE 3. Description of multimodal benchmark functions.

Function	Name [48]	Range	f_{min}	n (Dim)
$F_8(X) = \sum_{i=1}^{n} -x_i \sin(\sqrt{\lvert x_i \rvert})$	Generalized Schwefel's problem 2.26	$[-500, 500]^n$	$428.9829 \times n$	30
$F_9(X) = \sum_{i=1}^{n} [x_i^2 - 10\cos(2\pi x_i) + 10]$	Generalized Rastrigin's function	$[-5.12, 5.12]^n$	0	30
$F_{10}(X) = -20\exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}\right) - \exp\left(\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi x_i)\right) + 20 + e$	Ackley's function	$[-32, 32]^n$	0	30
$F_{11}(X) = \frac{1}{4000}\sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n} \cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$	Ackley's function	$[-600, 600]^n$	0	30
$F_{12}(X) = \frac{\pi}{n}\left\{10\sin(\pi y_1) + \sum_{i=1}^{n-1}(y_i - 1)^2[1 + 10\sin^2(\pi y_{i+1})] + (y_n - 1)^2\right\} + \sum_{i=1}^{n} u(x_i, 10, 100, 4)$ $y_i = 1 + \frac{x_{i+4}}{4}$ $u(x_i, a, k, m) =$ $\begin{cases} k(x_i - a)^m & x_i > a \\ 0 & a < x_i < a \\ k(-x_i - a)^m & x_i < -a \end{cases}$	Generalized penalized function	$[-50, 50]^n$	0	30
$F_{13}(X) = 0.1\left\{\sin^2(3\pi x_1) + \sum_{i=1}^{n}(x_i - 1)^2[1 + \sin^2(3\pi x_i + 1)] + (x_n - 1)^2[1 + \sin^2(2\pi x_n)]\right\} + \sum_{i=1}^{n} u(x_i, 5, 100, 4)$	Generalized penalized function	$[-50, 50]^n$	0	30

among the five algorithms are shown in bold. According to the results of these tables in the following subsections, the exploration, exploitation, and convergence rate of the new method are investigated using a comparative performance comparison of ATSA against four selected algorithms.

A. EXPLOITATION CAPABILITY

Unimodal test functions can be considered to investigate the exploitation capability of an optimization algorithm [49], [50]. In this study, to evaluate the ability of ATSA to exploit the promising regions, seven unimodal benchmark functions (F_1 to F_7) are solved and the results are compared with four selected optimization methods in Table 5. The results of this table show that, for all unimodal functions except F$_6$, ATSA could provide a better solution. In addition, for four functions (F_1-F_4), ATSA reached the global optima. It means that the new algorithm has a large potential search space compared with the other optimization algorithms.

B. EXPLORATION VERIFICATION

In order to evaluate the capability of an optimization algorithm to effectively explore the search space, multimodal benchmark functions that have many local optima are usually considered [49], [50]. Based on the presented procedure,

16 multimodal functions (F_8 to F_{23}) are minimized. According to the results of Tables 6 and 7, it can be observed that the best and mean values reached by ATSA for most of the functions (except F_{13}) are significantly better than the other methods. However, for F_{13}, the results are also comparable to the other algorithms. From the standard deviation point of view, which indicates the stability of the algorithm, the results show that ATSA is a more stable method when compared with the other techniques. From the analysis, it can be concluded that ATSA either outperforms the other algorithms or performs almost equivalently. The consistent performance of the new method for such a comprehensive suite of multimodal benchmark functions verifies its superior capabilities of exploration.

C. CONVERGENCE CAPABILITY

The convergence progress curves of ATSA for benchmark test functions are compared with TSA, GSA, SCA, and GWO in Figure 3. The curves are plotted against the number of function evaluations. The descending trend is quite evident in the convergence curve of ATSA on all of the test functions investigated. This strongly evidences the ability of the new algorithm to obtain a better approximation of the global optimum over the course of iterations. In addition, the curves of test functions show that ATSA is capable of exploring the

TABLE 4. Description of fixed-dimension multimodal benchmark functions.

Function	Name [48]	Range	f_{min}	n (Dim)
$F_{14}(X) = \left(\dfrac{1}{500} + \sum_{j=1}^{25} \dfrac{1}{j + (x_i - a_{ij})^6} \right)^{-1}$	Shekel's Foxholes function	$[-65.53, 65.53]^n$	1	2
$F_{15}(X) = \sum_{i=1}^{11} \left[a_i - \dfrac{x_1(b_i^2 + b_i x_2)}{b_i^2 + b_i x_3 + x_4} \right]^2$	Kowalik's function	$[-5, 5]^n$	0.00030	4
$F_{16}(X) = 4x_1^2 - 2.1x_1^4 + \dfrac{1}{3}x_1^6 + x_1 x_2 - 4x_2^2 + 4x_2^4$	Six-hump camel back function	$[-5, 5]^n$	-1.0316	2
$F_{17}(X) = \left(x_2 - \dfrac{5.1}{4\pi^2}x_1^2 + \dfrac{5}{\pi}x_1 - 6 \right)^2 + 10\left(1 - \dfrac{1}{8\pi}\right)\cos x_1 + 10$	Branin function	$[-5, 5]^n$	0.398	2
$F_{18}(X) = [1 + (x_1 + x_2 + 1)^2(19 - 14x_1 + 3x_1^2 - 14x_2 + 6x_1 x_2 + 3x_2^2)]$ $\times [30 + (2x_1 - 3x_2)^2$ $\times (18 - 32x_1 + 12x_1^2 + 48x_2 - 36x_1 x_2 + 27x_2^2)]$	Goldstein-Price function	$[-2, 2]^n$	3	2
$F_{19}(X) = -\sum_{i=1}^{4} c_i \exp\left(-\sum_{j=1}^{3} a_{ij}(x_j - p_{ij})^2 \right)$	Hartman's family	$[1, 3]^n$	-3.86	3
$F_{20}(X) = -\sum_{i=1}^{4} c_i \exp\left(-\sum_{j=1}^{6} a_{ij}(x_j - p_{ij})^2 \right)$	Hartman's family	$[0, 1]^n$	-3.32	6
$F_{21}(X) = -\sum_{i=1}^{5} [(X - a_i)(X - a_i)^T + c_i]^{-1}$	Shekel's family	$[0, 10]^n$	-10.1532	4
$F_{22}(X) = -\sum_{i=1}^{7} [(X - a_i)(X - a_i)^T + c_i]^{-1}$	Shekel's family	$[0, 10]^n$	-10.4028	4
$F_{23}(X) = -\sum_{i=1}^{10} [(X - a_i)(X - a_i)^T + c_i]^{-1}$	Shekel's family	$[0, 10]^n$	-10.5363	4

search space extensively and identifying the most promising region in fewer iterations. The obtained results indicate that the ATSA outperforms the other algorithms in most cases and has faster convergence to the best solution.

D. STATISTICAL SIGNIFICANCE ANALYSIS
In order to determine the statistical significance of the comparative results between two or more algorithms, a non-parametric pairwise statistical analysis should be conducted. As recommended by Derrac *et al.* [51], to assess meaningful comparison between the proposed and alternative methods, the nonparametric Wilcoxon's rank sum test is performed between the results. In this regard, utilizing the best results obtained from 30 runs of each method, a pair-wise comparison is conducted.

Wilcoxon's rank sum test returns p-value, sum of positive ranks ($R+$) and the sum of negative ranks ($R-$) [52]. Table 8 presents the results of Wilcoxon's rank sum test of ATSA when compared with other methods. The p-value indicates the minimum significance level for detecting differences. In this study, $\alpha = 0.05$ is considered as the level of significance. If the p-value of the given algorithm is greater than 0.05, then there is no significant difference between the two compared methods. Such a result is indicated with "N.A" in the winner rows of Table 8. On the other hand, if the p-value is less than α, it definitely means that, in each pair-wise comparison, the better result obtained by the best algorithm is statistically significant and was not gained by chance. In such cases, if the R+ is bigger than R-, indicates ATSA has a superior performance than the alternative method otherwise

TABLE 5. Results comparison of unimodal test functions.

Fun.	Index	ATSA	TSA	SCA	GSA	GWO
F_1	Best	**0.00**	5.1458e-61	1.5523e-07	1.001e-17	2.4915e-61
	Worst	**0.00**	1.1586e-54	0.0043	3.186e-17	3.8647e-58
	Mean	**0.00**	8.3155e-56	2.3458e-04	2.114e-17	4.9162e-59
	Median	**0.00**	7.1012e-58	1.9737e-05	2.007e-17	1.0534e-59
	Std.	**0.00**	2.4905e-55	7.9295e-04	5.815e-18	1.0230e-58
F_2	Best	**0.00**	1.1196e-35	1.5005e-09	1.528e-08	8.3612e-36
	Worst	**0.00**	3.2814e-32	9.8446e-06	3.331e-08	5.3488e-34
	Mean	**0.00**	2.1532e-33	1.6882e-06	2.393e-08	8.3658e-35
	Median	**0.00**	3.1044e-34	5.4000e-07	2.346e-08	5.9294e-35
	Std.	**0.00**	6.0237e-33	2.4046e-06	4.002e-09	9.8594e-35
F_3	Best	**0.00**	2.5684e-32	70.8285	102.955	1.2533e-19
	Worst	**0.00**	2.4492e-17	2.6762e+03	468.616	3.5572e-13
	Mean	**0.00**	8.1741e-19	789.1620	245.469	1.5096e-14
	Median	**0.00**	1.8696e-24	619.4506	221.115	2.0740e-17
	Std.	**0.00**	4.4714e-18	746.2287	100.102	6.5547e-14
F_4	Best	**0.00**	3.2458e-08	1.2610	2.249e-09	9.8174e-16
	Worst	**0.00**	6.3429e-05	35.6743	5.085e-09	2.4431e-13
	Mean	**0.00**	1.0102e-05	9.3080	3.303e-09	1.9487e-14
	Median	**0.00**	2.0270e-06	6.9806	3.202e-09	6.3817e-15
	Std.	**0.00**	1.6927e-05	8.0720	7.442e-10	4.4955e-14
F_5	Best	**0.122**	25.6273	27.3230	25.745	25.2273
	Worst	**8.171**	29.5430	49.5110	220.911	28.7294
	Mean	**2.337**	28.4422	29.9106	42.2647	26.9256
	Median	**0.721**	28.8115	29.0097	26.1443	27.1173
	Std.	**2.772**	0.7616	4.1508	45.4674	0.8418
F_6	Best	1.9836e-07	2.0585	3.4070	**9.711e-18**	0.2466
	Worst	0.0220	4.7791	4.4435	**8.645e-16**	1.2619
	Mean	0.0021	3.6724	4.0360	**3.097e-17**	0.6376
	Median	1.9836e-07	3.5615	4.0572	**2.953e-17**	0.7452
	Std.	0.0056	0.6918	0.2954	**6.165e-18**	0.3353
F_7	Best	3.3002e-10	6.7114e-04	0.0015	0.0061	1.5222e-04
	Worst	**1.2212e-04**	0.0036	0.0431	0.0462	0.0022
	Mean	**7.2800e-06**	0.0018	0.0116	0.0237	7.9976e-04
	Median	**3.3002e-10**	0.0018	0.0078	0.0222	7.0098e-04
	Std.	**2.4887e-05**	7.7268e-04	0.0101	0.0098	4.6287e-04

TABLE 6. Results comparison of multimodal test functions.

Fun	Index	ATSA	TSA	SCA	GSA	GWO
F_8	Best	**-1.256e+04**	-7.892e+03	-5.299e+03	-3.627e+03	-8.817e+03
	Worst	**-1.256e+04**	-5.271e+03	-3.532e+03	-2.003e+03	-4.974e+03
	Mean	**-1.256e+04**	-6.616e+03	-4.076e+03	-2.782e+03	-6.252e+03
	Median	**-1.256e+04**	-6.611e+03	-3.972e+03	-2.746e+03	-6.227e+03
	Std.	**1.864**	599.2609	336.8249	365.4671	852.4634
F_9	Best	**0.00**	77.7761	1.0560e-06	8.9546	0.00
	Worst	**0.00**	254.9883	51.4451	21.8891	10.0548
	Mean	**0.00**	151.4539	5.9694	15.6209	0.8853
	Median	**0.00**	149.6596	9.3391e-04	15.9193	0.00
	Std.	**0.00**	35.8717	12.2476	3.1043	2.4438
F_{10}	Best	**8.8818e-16**	1.5099e-14	1.5579e-05	2.528e-09	1.1546e-14
	Worst	**8.8818e-16**	4.3125	20.2198	4.482e-09	2.2204e-14
	Mean	**8.8818e-16**	2.4095	14.3622	3.491e-09	1.5928e-14
	Median	**8.8818e-16**	2.9381	20.1275	3.476e-09	1.5099e-14
	Std.	**0.00**	1.3920	8.9778	5.153e-10	2.5861e-15
F_{11}	Best	**0.00**	0.00	4.8381e-07	1.6952	0.00
	Worst	**0.00**	0.0159	0.7703	10.6642	0.0140
	Mean	**0.00**	0.0077	0.1368	4.2510	0.0014
	Median	**0.00**	0.0082	0.0032	3.5667	0.00
	Std.	**0.00**	0.0057	0.2218	2.0234	0.0041
F_{12}	Best	**2.168e-06**	0.2738	0.2631	8.203e-02	0.0121
	Worst	**0.0022**	13.8088	5.6300	0.1037	0.0920
	Mean	**6.989e-04**	6.3735	0.9568	0.0198	0.0364
	Median	**5.342e-05**	6.7411	0.4964	1.3512	0.0329
	Std.	**6.822e-04**	3.4586	1.1497	0.0400	0.0201
F_{13}	Best	2.6099e-05	1.7796	1.8452	**1.340e-18**	0.1006
	Worst	9.1819e-04	4.1077	22.5849	**0.0110**	1.0416
	Mean	**5.0093e-04**	2.8976	3.4211	7.324e-04	0.5280
	Median	5.1139e-04	2.8914	2.3552	**2.068e-18**	0.5238
	Std.	**4.2513e-04**	0.6436	3.9911	0.0028	0.2359

TABLE 7. Results comparison of fixed-dimension multimodal test functions.

Fun	Index	ATSA	TSA	SCA	GSA	GWO
F_{14}	Best	**0.9980**	**0.9980**	**0.9980**	**0.9980**	**0.9980**
	Worst	**0.9980**	12.6705	2.9821	8.0858	12.6705
	Mean	**0.9980**	7.6657	1.1964	3.6212	4.1312
	Median	**0.9980**	10.7632	0.9980	3.0452	2.9821
	Std.	**1.477e-11**	4.8845	0.6054	2.1942	4.1443
F_{15}	Best	3.138e-04	3.751e-04	3.4063e-04	0.0012	3.1749e-04
	Worst	**3.968e-04**	0.0566	0.0014	0.0118	0.0204
	Mean	**3.364e-04**	0.0043	8.5975e-04	0.0025	0.0044
	Median	**3.232e-04**	4.539e-04	7.3095e-04	0.0021	3.0754e-04
	Std.	**2.458e-05**	0.0116	3.8089e-04	0.0019	0.0081
F_{16}	Best	**-1.0316**	-1.0316	**-1.0316**	**-1.0316**	**-1.0316**
	Worst	**-1.0316**	-1.0000	**-1.0316**	**-1.0316**	**-1.0316**
	Mean	**-1.0316**	-1.0306	**-1.0316**	**-1.0316**	**-1.0316**
	Median	**-1.0316**	-1.0316	**-1.0316**	**-1.0316**	**-1.0316**
	Std.	1.859e-06	0.0058	1.0395e-05	5.608e-05	**4.7385e-09**
F_{17}	Best	**0.3979**	0.3979	0.3979	**0.3979**	**0.3979**
	Worst	0.4011	0.3980	0.3992	**0.3979**	**0.3979**
	Mean	0.3987	0.3979	0.3982	**0.3979**	**0.3979**
	Median	0.3985	0.3979	0.3981	**0.3979**	**0.3979**
	Std.	7.939e-04	1.371e-05	3.4881e-04	0	1.1055e-06
F_{18}	Best	**3.000**	**3.000**	**3.000**	**3.000**	**3.000**
	Worst	3.005	84.00	**3.000**	**3.000**	**3.000**
	Mean	3.002	5.700	**3.000**	**3.000**	**3.000**
	Median	3.002	3.000	**3.000**	**3.000**	**3.000**
	Std.	1.702e-05	14.7885	5.3498e-06	**1.592e-15**	9.5052e-06
F_{19}	Best	**-3.8628**	**-3.8628**	-3.8625	**-3.8628**	**-3.8628**
	Worst	**-3.8628**	-3.8549	-3.8539	**-3.8628**	-3.8539
	Mean	**-3.8628**	-3.8625	-3.8560	**-3.8628**	-3.8620
	Median	**-3.8628**	-3.8628	-3.8548	**-3.8628**	-3.8628
	Std.	**1.362e-16**	0.0014	0.0029	2.479e-05	0.0022
F_{20}	Best	**-3.3220**	-3.3216	-3.1918	**-3.3220**	**-3.3220**
	Worst	**-3.3220**	-3.0885	-2.0488	**-3.3220**	-3.0292
	Mean	**-3.3220**	-3.2538	-3.0155	**-3.3220**	-3.2493
	Median	**-3.3220**	-3.2028	-3.0139	**-3.3220**	-3.2625
	Std.	**1.355e-16**	0.0671	0.1974	**1.355e-15**	0.0821
F_{21}	Best	**-10.1532**	-10.1361	-8.1370	**-10.1532**	-10.1531
	Worst	**-10.1532**	-2.6669	-0.8802	-2.6829	-5.0999
	Mean	**-10.1532**	-7.2879	-4.3187	-6.3969	-9.4790
	Median	**-10.1532**	-7.4198	-4.9053	-3.9547	-10.1526
	Std.	**2.499e-07**	2.8594	2.0785	3.5901	1.7469
F_{22}	Best	**-10.4028**	-10.3812	-9.0513	-10.4009	-10.4029
	Worst	**-10.4028**	-2.7427	-0.9074	-10.4029	-5.0877
	Mean	**-10.4028**	-7.8325	-5.4154	-10.4029	-10.2253
	Median	**-10.4028**	-10.2554	-5.0380	-10.4028	-10.4025
	Std.	**5.420e-15**	3.1843	1.7315	4.664e-06	0.9703
F_{23}	Best	**-10.5363**	-10.5193	-9.3851	-10.5364	**-10.5363**
	Worst	**-10.5362**	-1.6752	-3.2531	-10.5364	-10.5354
	Mean	**-10.5363**	-7.6730	-5.2925	-10.5364	-10.5359
	Median	**-10.5363**	-10.4114	-5.0398	-10.5364	-10.5360
	Std.	**2.485e-05**	3.7585	1.0982	1.836e-15	2.5855e-04

ATSA has inferior performance and alternative algorithm shown better performance [53].

According to the results of Wilcoxon's rank sum test in Table 8, the pairwise comparison between ATSA and GSA reveals that in the optimization of 23 test functions, the new method has superior performance in 19 cases and has inferior performance in two cases. In addition, for F_{16} and F_{20}, both methods are statistically equivalent. Similarly, in the other pairwise comparison, for the majority of the test suite,

ATSA provides better results. Therefore, the nonparametric statistical analysis proves that ATSA generated significantly better solutions and, comparatively, has superior performance over the other algorithms.

As the results show, the ATSA is capable of conducting a full investigation of the search area and promptly identifying the most promising position. Based on the findings, it can be inferred that ATSA outperforms the original algorithm as well as alternative optimization methods.

VI. MODEL APPLICATION

In this section, the optimum design of an interior spread footing in dry sand is conducted using the proposed ATSA by considering two objective functions: CO_2 emission and construction cost. This problem has been solved previously by Camp and Assadollahi [45] using a hybrid big bang-big crunch (BB-BC) algorithm. The input parameters for the case study are given in Table 9.

The problem is solved by the presented procedure for both the cost and CO_2 objective functions. In order to verify the efficiency of the proposed ATSA method, the analysis
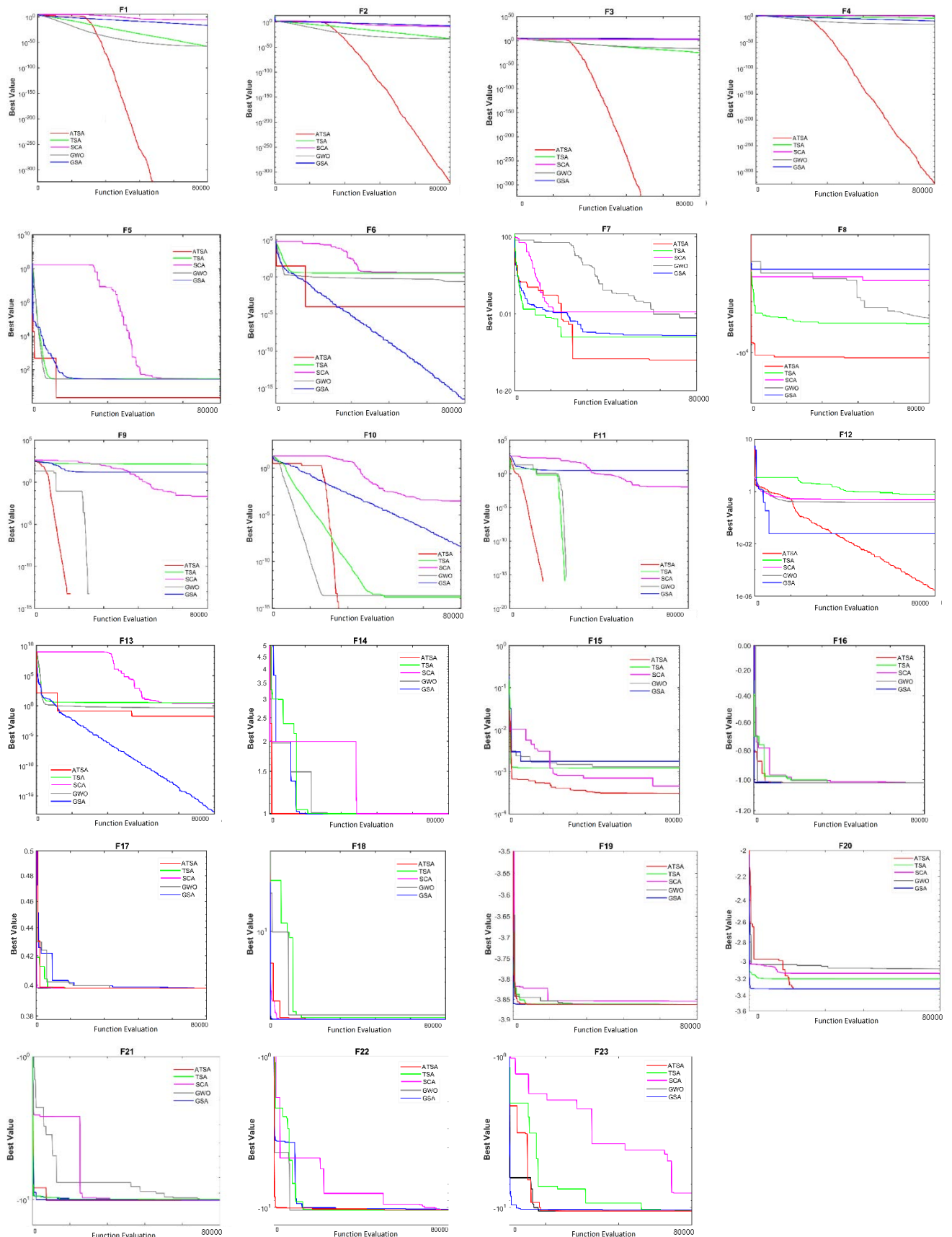
FIGURE 3. Convergence curve of test functions.

TABLE 8. Results of Wilcoxon's rank sum test.

Fun	Wilcoxon test Parameters	ATSA vs TSA	ATSA vs GSA	ATSA vs SCA	ATSA vs GWO
F1	p-value	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06
	R+	465	465	465	465
	R-	0	0	0	0
	Winner	ATSA	ATSA	ATSA	ATSA
F2	p-value	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06
	R+	465	465	465	465
	R-	0	0	0	0
	Winner	ATSA	ATSA	ATSA	ATSA
F3	p-value	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06
	R+	465	465	465	465
	R-	0	0	0	0
	Winner	ATSA	ATSA	ATSA	ATSA
F4	p-value	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06
	R+	465	465	465	465
	R-	0	0	0	0
	Winner	ATSA	ATSA	ATSA	ATSA
F5	p-value	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06
	R+	465	465	465	465
	R-	0	0	0	0
	Winner	ATSA	ATSA	ATSA	ATSA
F6	p-value	1.7344E-06	7.4523E-7	1.7344E-06	2.353E-06
	R+	465	0	465	462
	R-	0	465	0	3
	Winner	ATSA	GSA	ATSA	ATSA
F7	p-value	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06
	R+	465	465	465	465
	R-	0	0	0	0
	Winner	ATSA	ATSA	ATSA	ATSA
F8	p-value	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06
	R+	465	465	465	465
	R-	0	0	0	0
	Winner	ATSA	ATSA	ATSA	ATSA
F9	p-value	1.7344E-06	1.7344E-06	1.7344E-06	0.02
	R+	465	465	465	21
	R-	0	0	0	0
	Winner	ATSA	ATSA	ATSA	ATSA
F10	p-value	1.73E-06	1.73E-06	1.73E-06	1.73E-06
	R+	465	465	465	465
	R-	0	0	0	0
	Winner	ATSA	ATSA	ATSA	ATSA
F11	p-value	1.473E-03	1.73E-06	1.73E-06	0.068
	R+	91	465	465	10
	R-	0	0	0	0
	Winner	ATSA	ATSA	ATSA	N.A
F12	p-value	1.73E-06	1.73E-06	1.73E-06	1.73E-06
	R+	465	465	465	465
	R-	0	0	0	0
	Winner	ATSA	ATSA	ATSA	ATSA
F13	p-value	1.73E-06	3.74E-04	1.73E-06	1.73E-06
	R+	465	66	465	465
	R-	0	399	0	0
	Winner	ATSA	GSA	ATSA	ATSA
F14	p-value	4.81E-06	1.73E-06	2.56E-06	3.22E-04
	R+	403	465	435	152
	R-	3	0	0	1
	Winner	ATSA	ATSA	ATSA	ATSA
F15	p-value	0.006	1.73E-06	2.35E-06	0.393
	R+	366	465	462	274
	R-	99	0	3	191
	Winner	ATSA	ATSA	ATSA	N.A
F16	p-value	0.132	0.059	0.371	1.59E-06
	R+	50	304	276	0
	R-	415	161	189	465
	Winner	N.A	N.A	N.A	GWO
F17	p-value	1.73E-06	1.37E-06	3.18E-06	1.73E-06
	R+	465	465	465	0
	R-	0	0	0	465
	Winner	ATSA	ATSA	ATSA	GWO
F18	p-value	3.11E-05	1.08E-06	1.73E-06	1.73E-06
	R+	30	0	0	0
	R-	435	465	465	465
	Winner	ATSA	GSA	SCA	GWO
F19	p-value	1.73E-06	8.38E-08	1.73E-06	1.73E-06
	R+	465	465	465	465
	R-	0	0	0	0
	Winner	ATSA	ATSA	ATSA	ATSA
F20	p-value	1.73E-06	0.894	1.73E-06	1.73E-06
	R+	465	239	465	465
	R-	0	226	0	0
	Winner	ATSA	N.A	ATSA	ATSA
F21	p-value	1.73E-06	0.046	1.73E-06	1.73E-06
	R+	465	329	465	465
	R-	0	136	0	0
	Winner	ATSA	ATSA	ATSA	ATSA
F22	p-value	1.73E-06	1.44E-07	1.73E-06	2.13E-06
	R+	465	465	465	463
	R-	0	0	0	2
	Winner	ATSA	ATSA	ATSA	ATSA
F23	p-value	1.73E-06	1.46E-05	1.73E-06	3.51E-6
	R+	465	435	465	458
	R-	0	30	0	7
	Winner	ATSA	ATSA	ATSA	ATSA
Total	Superior/Inferior/N.A	22/0/1	19/2/2	21/1/1	18/3/2

TABLE 9. Input parameters for the case study [45].

| Parameter	Unit	Symbol	Value
Effective friction angle of base soil	degree	ϕ	35
Unit weight of base soil	kN/m^3	γ_s	18.5
Young's modulus	MPa	E	50
Poisson's ratio	—	v	0.3
Vertical load	kN	P	3000
Moment	kN-m	M	0.0
Concrete cover	cm	d_c	7.0
Over excavation length	m	L_0	0.3
Over excavation width	m	B_0	0.3
Yield strength of reinforcing steel	MPa	f_y	400
Compressive strength of concrete	MPa	f_c	30
Factor of safety for bearing capacity	—	FS	3.0
Allowable settlement of footing	mm	δ_{all}	25
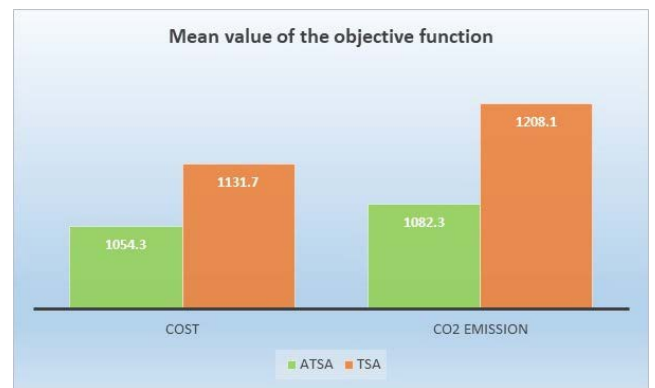
FIGURE 4. Average values of the objective functions.

results are compared with the standard TSA as well as BB-BC algorithms [45]. In this experiment, the maximum number of function evaluations is considered equal to 50,000. Both the TSA and ATSA algorithms are run 30 times, and the best results of the analyses for the minimum cost and minimum CO_2 emission obtained by each method are presented in Table 10.

The findings presented in Table 10 show that the optimum design evaluated by the proposed ATSA algorithm is lower than those evaluated by standard TSA and BB-BC techniques. According to the result, the best price obtained by ATSA is 1046.8\$, which is almost 4.8% lower than the best price calculated by TSA and 3.7% lower than the BB-BC's result, which means the new method could provide a cheaper design. In addition, the best value of the CO_2 objective function calculated by the new algorithm is almost 7.2% and 4.2% lower than those evaluated by the TSA and BB-BC methods, respectively.

TABLE 10. Optimization result for spread footing optimization.

Design variable	Unit	Optimum Value					
		Best Cost Results			Best CO_2 Emission Results		
		ATSA	TSA	BB-BC[45]	ATSA	TSA	BB-BC[45]
X_1	m	2.322	2.268	2.3	2.167	2.488	2.10
X_2	m	1.623	1.659	1.86	1.666	1.581	2.09
X_3	m	0.498	0.498	0.6	0.494	0.502	0.6
X_4	m	1.623	2.0	1.3	1.665	1.58	1.26
X_5	cm^2	44	42	-	39	48	-
X_6	cm^2	23	24	-	25	22	-
Best Value of the Objective Function		1046.8$	1099.6$	1086$	1072.4 kg	1156.3 kg	1119.53
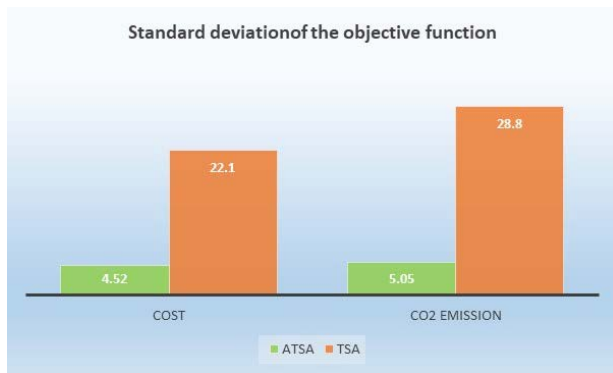
FIGURE 5. Standard deviation of the results.

FIGURE 6. Convergence of TSA and ATSA for cost function.

FIGURE 7. Convergence of TSA and ATSA for CO_2 function.

Figures 4 and 5 illustrate the average and standard deviation of the cost and CO_2 objective functions from 30 different runs, respectively. Based on these findings, the mean values of the objective functions acquired by ATSA are lower than those obtained by TSA. Furthermore, the standard deviation of the ATSA results is much smaller than that of the original method, demonstrating that the ATSA significantly improves the TSA's instability.

The convergence progress curves of ATSA for cost and CO_2 objective functions are compared to those of TSA in Figurs 6 and 7. As shown in these figures, the ATSA is capable of exploring the search space extensively and identifying the most promising region in fewer iterations because of its effective modifications. From the above results, it can be inferred that ATSA outperforms the original algorithm and the findings confirm the effectiveness of the new algorithm for optimization of spread foundations.

In the last part of this section, a sensitivity analysis is carried out to investigate the effects of soil parameters on the spread foundation design. Ground conditions and soil characteristics influence geotechnical engineering designs. As a result, a comprehensive site study is required to determine the ground conditions and design input parameters. In order
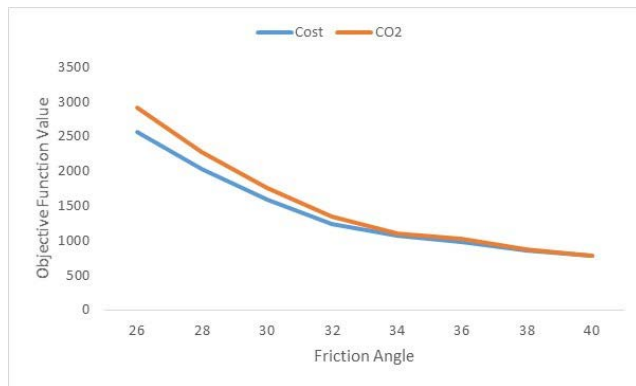
FIGURE 8. Effects of ϕ variation on the cost and CO_2 emission.
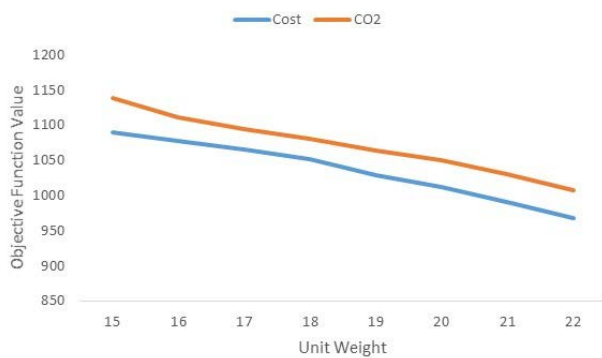

FIGURE 9. Effects of γ variation on the cost and CO_2 emission.

to explore the effect of soil parameters on the final design, the total construction cost and CO_2 emission of the foundation are computed by different values of effective friction angle (ϕ) and unit weight of soil (γ). Figure 8 shows the low-cost and low-CO_2 emission designs of a foundation for different values of ϕ as the internal friction angle of the soil varies from 26 to 40 degrees. As shown in Figure 8, Over this range, the construction cost and CO_2 emissions decrease drastically as the friction angle of the soil (ϕ) increases. However, if ϕ becomes greater than 34, the intensity of variation will be reduced.

In the second stage, the total construction cost and CO_2 emissions are obtained using different values of unit weight of soil while the other properties are kept fixed. The results are shown graphically in Figure 9 and indicate that increasing the soil's unit weight (γ) from 15 to 22 KN/m^3 reduces the total price and CO_2 emissions by nearly 12%.

The findings show that variations in effective friction angle have the greatest effects on total cost and CO_2 emissions, and that this parameter is critical in the optimal design of spread foundation. In other words, this parameter should be measured as accurately as possible during the site investigation.

VII. CONCLUSION

In this paper, two main contributions are presented: (i) a novel adaptive version of the tunicate swarm algorithm called ATSA is introduced and verified using a set of

23 mathematical test functions of the well-known CEC 2017; and (ii) the proposed ATSA is applied for the low-cost and low-CO_2 emission design of shallow foundations. The proposed method has the potential to increase the TSA's exploration ability while also preventing it from becoming trapped in a local minima location. The new method's performance is evaluated using a combination of unimodal and multimodal benchmark functions. According to the results and findings, In terms of finding the global solution for most unimodal and multimodal functions, ATSA outperforms standard TSA as well as other approaches, In the next step, the proposed ATSA is applied to the optimum design of the shallow foundation. The performance of the new algorithm for the minimization of construction costs and CO_2 emissions of the foundation is investigated by considering a case study from the literature. When compared to existing algorithms, the findings indicate that the newly proposed method is quite robust and efficient for optimum design of spread foundations. Finally, a sensitivity analysis reveals the importance of the internal friction angle of the soil on the final construction cost and CO_2 emissions.

There are several potential applications and research directions that can be recommended for future work. Many engineering problems can be solved using the proposed algorithm, including structural optimization, damping controller design for power system oscillations, image processing, pipe routing design, optimal power flow problems, resource scheduling, and neural network training.

Like all stochastic optimization techniques, one of the limitations of the proposed ATSA is that new optimizers may be developed in the future that will perform better than ATSA in some real applications. Additionally, due to the stochastic nature of the ATSA, it cannot be guaranteed that the solutions obtained using the ATSA for optimization problems are exactly equal to the global optimum for all optimization problems.

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