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RESEARCH ARTICLE

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Optimum design of post-tensioned axially symmetric cylindrical walls using novel hybrid metaheuristic methods

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Summary

An efficient methodology for various structural design problems is needed to optimize the total cost for structures. Although some methods seem to be efficient for applications, due to using special algorithm parameters, computational cost, and some other reasons, there is still much to be done in order to develop an effective method for general design applications. This paper describes the influence of the selected procedure on the design of cost-optimized, post-tensioned axially symmetric cylindrical reinforced concrete walls. In this study, the optimum design of axially symmetric cylindrical walls using several metaheuristic algorithms is investigated. The new generation algorithms used in the study are flower pollination algorithm, teaching–learning-based optimization, and Jaya algorithm (JA). These algorithms are also compared with one of the previously developed algorithm called harmony search. The numerical examples were done for walls with 4- to 10-m height and for 1, 5, 10, 15, 20, and 25 post-tensioned load cases, respectively. Several independent runs are conducted, and in some of these runs, JA may trap to a local solution. To overcome this situation, hybrid algorithms such as JA using Lévy flights, JA using Lévy flights with probabilistic student phase (JALS), JA using Lévy Flights with consequent student phase (JALS2), and JA with probabilistic student phase are developed. It is seen that in many respects, the JALS2 and JALS are the most effective within the proposed hybrid approaches.

KEYWORDS

cost optimization cylindrical walls, flower pollination algorithm, hybrid algorithm analyses of cylindrical walls, Jaya algorithm, teaching–learning-based optimization

1 | INTRODUCTION

Engineering designs are based on two main objectives. These two objectives, defined as safety and cost, are two opposing concepts, when one is increasing, the other one is decreasing. If all parameters belonging to these two purposes are formulated, it may be possible to obtain a solution that simultaneously provides these two goals with mathematical operations. This may not be always possible or easy task in some cases such as design of structural systems, in which many parameters affect each other. For four decades, metaheuristic algorithms have been widely used to perform this task. The most important reason why algorithms are used so widely is that not only the ability of solving problems that are difficult or impossible to express mathematically but also easily applying of these algorithms to the problems without using complex mathematical functions.

From the first day to the present, a considerable number of metaheuristic algorithm has been proposed. Looking at the number of algorithms, it brings out questions such as what the reason is, why so many algorithms are proposed, are the algorithms insufficient to achieve the optimization task, if so, why more algorithms are suggested, and if algorithms are successful what is the measure of success. These questions can be further diversified. The answer to these questions can be found in scientific researchers on algorithms.

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After the first introduction of the algorithms, some additional studies are done, and these studies are generally about adjusting the parameters proposed for the algorithm to improve the performance of algorithms. As it is understood from the previous studies, the parameters not only depend on the optimization example but also directly affect the performance of the algorithm. Therefore, to obtain best algorithm performance for a problem, it is necessary to conduct analyses to adjust the parameters of the algorithm. It is a hard work that requires experience.

After the experience gained from each of study, it is to be understood that the algorithms tend to be user-friendly by using fewer parameters, over time. For instance, in the particle swarm optimization[1] proposed in 1995: the number of special algorithm parameters is three; in the differential evaluation[2] algorithm suggested in 1997: the number of parameters is two; in the harmony search (HS)[3] algorithm presented in 2001: the number of parameters is two; and in the flower pollination algorithm (FPA)[4] proposed in 2012: only one algorithm parameter is used. Finally, two recent algorithms such as teaching–learning-based optimization (TLBO)[5] and Jaya algorithm (JA)[6] without user-defined parameters are proposed.

Whether the employed algorithm is a new or an old proposed algorithm, the common practice is to compare its performance for practical use. From the algorithms, the success or performance of the algorithm is decided by looking at some values obtained as the result of analysis. Although various values are used to compare the performance of algorithms in the scientific studies, parameters such as minimum value, mean value, standard deviation, and analysis number are frequently used. As a result, the focus of whole scientific research is to find more easily applicable algorithms and obtain better performance for optimization problems.

Several mechanical and civil engineering problems are the subject of structural optimization, and the optimization problems include vehicle engine connecting rod,[7] lightweight design of an automobile hinge component,[8] optimal machining parameters in manufacturing processes,[9] mechanical and structural design problems,[10] crashworthiness optimization of vehicle thin-walled tubes,[11] automotive floor frame,[12] shape optimization,[13] structural design optimization,[14] topology synthesis multicomponent structural assemblies,[15] turning operations,[16] thin-wall structures,[17] structural design of vehicle components,[18] vehicle components,[19] vehicle crashworthiness,[20] optimal design of structures for earthquake loading,[21] shape optimization of arch dams,[22] layout optimization of truss structures,[23] optimal placement of steel plate shear walls,[24] seismic layout optimization of steel braced frames,[25] and structural control systems such as dampers.[26–31]

The number of developed methodologies on optimum design of reinforced concrete (RC) liquid tanks is limited.[32–41] In terms of contributing to this work, in this study, the optimum design of axially symmetric cylindrical walls is presented by using several new generation metaheuristic algorithms. These new generation algorithms are FPA, TLBO, and JA. These three algorithms are new in the field of structural engineering. TLBO and JA are chosen as parameter-free algorithms. FPA has only one parameter in choosing the type of the optimization. The performance of these algorithms is compared with one of the widely used algorithms—HS. The algorithm performances are compared for different cases with various numbers of post-tensioned load and wall heights. In these cases, it is aimed to investigate the effect of the design variable number and width of solution range on algorithm performances. In some of these analyses, algorithms may have trap a local optimum value. To overcome this problem, four user-friendly hybrid algorithms such as JA using Lévy flights (JAL), JA using Lévy flights with probabilistic student phase (JALS), JA using Lévy flights with consequent student phase (JALS2) and JA with probabilistic student phase (JAS) are also proposed. Considering the performance of the proposed hybrid methods, it is thought that the methods may be a useful guide for future scientific studies.

2 | GENERAL THEORY OF CIRCULAR CYLINDRICAL SHELL LOADED SYMMETRICALLY WITH RESPECT TO ITS AXIS

The problem of circular cylindrical shells under the symmetrically distributed forces with respect to the cylinder axis is frequently encountered one in practical engineering applications. The stress distribution in boilers subjected the steam pressure; stresses in cylindrical containers under the internal liquid loads and the stress distribution of cylindrical pipes under uniform internal pressure are examples of these applications.

To establish the required equations for the solution of the problem, the equations of equilibrium on a small element of the shell (Figure 1) is considered. From the symmetry, it can be inferred that the membrane shearing forces ($N_{x\varphi} = N_{\varphi x}$) and twisting moments ($M_{x\varphi} = M_{\varphi x}$) are vanished. In these cases, forces N_φ and bending moments M_φ are constant along the circumference. From the symmetry, it can be also understood that within the transverse shearing forces, only the Q_x forces do not vanish.

Thus, three of the six equilibrium equations of the shell element are satisfied under the symmetry conditions. Assuming that external forces consisted only pressure normal to the surface, the remaning three equations can be written as

$$\frac{dN_x}{dx} r\,dx\,d\phi = 0,\ \frac{dQ_x}{dx} r\,dx\,d\phi + N_\phi\,dx\,d\phi + q\,r\,dx\,d\phi = 0,\quad \text{and} \frac{dM_x}{dx} r dx\,d\phi - Q_x\,r\,dx\,d\phi = 0\ . \tag{1}$$

The first expression of Equation (1) indicates that the N_x forces are constant. These forces are taken as zero for further calculations. In case of being different from zero, deformation and stresses correspond to these constant forces, which can be easily calculated and superposed with the rest loads.[42] The other equations can be written in the following simplified form:

$$\frac{dQ_x}{dx} + \frac{1}{r} N_\phi = -q \ \text{ and } \ \frac{dM_x}{dx} - Q_x = 0. \tag{2}$$

As seen in the Equation (2), there are three unknown forces; N_φ, Q_x and M_x that must be determined for solution. In order to identify these quantities, it can be considered that the displacements of points are at the middle surface of the shell. Because of symmetry, the displacement in

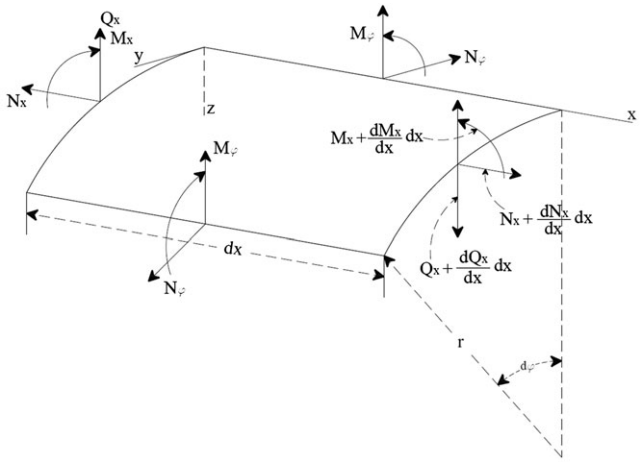

FIGURE 1 A small element of cylindrical wall

the circumferential direction vanishes. Therefore, the expressions for the remaining strain components u (in x direction) and w (in z direction) become

$$\varepsilon_x = \frac{du}{dx} \text{ and } \varepsilon_\phi = -\frac{w}{r}. \tag{3}$$

By considering the Hook's principle, it can be obtained as follows:

$$N_x = \frac{Eh}{1-v^2}(\varepsilon_x + v\varepsilon_\phi) = \frac{Eh}{1-v^2}\left(\frac{du}{dx} - v\frac{w}{r}\right) = 0 \text{ and } N_\phi = \frac{Eh}{1-v^2}(\varepsilon_\phi + v\varepsilon_x) = \frac{Eh}{1-v^2}\left(-\frac{w}{r} + v\frac{du}{dx}\right). \tag{4}$$

In the Equation (4), v is Poisson ratio, h is thickness of the shell, E is elasticity modulus, and r represents radius of the wall. By using expressions given in Equation (4), Equation (5) can be written as

$$\frac{du}{dx} = v\frac{w}{r} \text{ and } N_\phi = -\frac{Ehw}{r}. \tag{5}$$

From the symmetry, it can be concluded that there is no change in curvature in the circumferential direction. By considering the expressions used for plates, the moments obtain as

$$M_\phi = vM_x \text{ and } M_x = -D\frac{dw^2}{dx^2}, \quad \text{where } D = \frac{Eh^3}{12(1-v^2)} \tag{6}$$

represents flexural rigidity of the shell. By eliminating Q_x from Equation (2) and using Equations (5) and (6), problems of symmetrical deformation of circular cylindrical shells reduce to Equation (7).

$$\frac{d^2}{dx^2}\left(D\frac{d^2w}{dx^2}\right) + \frac{Eh}{r^2}w = q \tag{7}$$

Under the conditions of constant shell thickness (h), Equation (7) becomes

$$\frac{d^4w}{dx^4} + 4\beta^4 w = \frac{q}{D}, \quad \text{where } \beta^4 = \frac{Eh}{4r^2D} = \frac{3(1-v^2)}{r^2h^2}, \tag{8}$$

and general solution of this equaiton is

$$w = e^{\beta x}(C_1\cos\beta x + C_2\sin\beta x) + e^{-\beta x}(C_3\cos\beta x + C_4\sin\beta x) + f(x), \tag{9}$$

in which $f(x)$ represents a particular solution of the equation and C_1, C_2, C_3, and C_4 are the integration constants, which must be determined from the support conditions at the end of the cylinder. This equation is the same as beam on elastic foundation with flexural rigidity D and submitted to the action of load of intensity q.[42,43] This means the solution applied for beams on elastic foundation can be used for cylindrical shells and vice versa. In this paper, the superposition method [44] is applied for the solution of Equation (9) because of some advantages compared with others, that is, the number of mathematical operations and easy application to the general problem. Further information about the analyses methodology (superposition method) used in iterations can be found in previous studies.[39–41]

3 | OPTIMIZATION PROCESS VIA NEW GENERATION METAHEURISTIC ALGORITHM

The design variables of the problem are intensities of post-tensioning forces (X_1, X_2, ..., X_i, ..., and X_n), distances from the wall bottom (locations) of the post-tensioning forces (X_{n+1}, X_{n+2}, ..., X_{n+i}, ..., and X_{2n}), the thickness of the wall (X_{2n+1}), bar size and center to center spacing of the bars in horizontal direction (X_{2n+2} and X_{2n+3}) and in vertical direction (X_{2n+4} and X_{2n+5}), and compressive strength of concrete (X_{2n+6}) used in design. In other words, if n number of post-tensioning loads is used in design, the total number of design variables will be $2n + 6$.

A suitable RC design must satisfy all safety requirements defined in regulation. In this study, the rules of American Concrete Institute are considered (ACI 318: Building code requirements for structural concrete).[45] According to these rules, factored flexural moment (M_u), shear (V_u), and axial tension (T_u) at sections due to externally applied loads must be less than related strength capacities (M_d, V_d, and T_d) of the sections. Also, some limitations (upper and lower limits) for steel ratio (ρ), crack width (w), bar spacing (S), and concrete cover (c_c) are defined for the RC design in the regulation. All these design constraints can be seen in Table 1.

The objective function is to minimize total construction cost value given in Equation (10).

$$\min f(X) = C_c V_c + C_s W_s + C_{pt} W_{pt} + C_{fw} A_{fw} \tag{10}$$

In Equation (10), C_c is unit cost of concrete, V_c is total concrete volume, C_s represents unit cost steel reinforcement, W_s represents total weight of the steel reinforcements, C_{pt} is unit cost of post-tensioning cables, W_{pt} is total weight of the post-tensioning cables, C_{fw} represents labor cost per unit surface area, and A_{fw} represent total surface area. It must be noted that some additional expenses such as average transportation cost, concrete pump cost, and pouring cost of concrete are included in the unit costs. If the designer does not consider extras in the unit prices, then Equation (10) must be revised containing the relevant values.

In the present study, several new generation metaheuristic algorithms such as FPA,[4] TLBO,[5] and JA[6] were used for optimum design process. Also, to overcome trapping local solution problem, four different hybrid algorithms that contain some features of FPA and TLBO algorithms are proposed. The performance and robustness of proposed methods were also compared with one of the previously developed and frequently used algorithm HS.[3] In this section, the new generation metaheuristic algorithms and hybrids of JA are briefly explained.

A general flowchart for metaheuristic algorithms is given in Figure 2. According to this scheme, the optimization process via metaheuristic algorithms can be divided into five steps. In general sense, four of these five steps are approximately the same for all algorithms. Only the fourth step that contains generation of new solutions is the unique part of the algorithms. In this step, each algorithm produces a new solution with the help of equations developed according to its inspiration. By the help of these equations, the design variables and objective function converge to the optimum values. In other words, this step as well as these equations determines the performance of algorithms; that is, whether the algorithm are effective for the problem or not.

Step 1: The optimization problem is defined with height and radius of wall, loading conditions, and material properties (compressive and tensile strength, modulus of elasticity, Poisson ratio, specific gravities, unit costs, and so forth) in this section. Design variables (for n number of post-tensioning loads, the total number of variables are $2n + 6$), solution ranges (for X_i, i symbolizes ith design variable; X_i^{max} represent the upper limit, and X_i^{min} represent the lower limit), maximum iteration number (itermax) as stopping criteria, and special algorithm parameters (if exist) are also defined. Algorithm parameters are harmony memory size (HMS), harmony memory considering rate (HMCR) and pitch adjusting rate (PAR) for HS, pollen number (pn) and switch probability (sp) for FPA, population number (pn) for TLBO and JA algorithm. Although named differently, HMS and pn symbolize the number of solution vectors for all algorithms. Similarly, due to having two options for generating a new solution in HS and FPA algorithms, HMCR (for HS) and sp (for FPA) are related parameters used for making the decision in which way to produce the new solution.

Step 2: In this step, initial solution matrix (SM) is generated between upper (X_i^{max}) and lower (X_i^{min}) limits randomly as

$$X_i^{min} \le X_i = X_i^{min} + \text{rand}(0,1)\left(X_i^{max} - X_i^{min}\right) \le X_i^{max} \quad i = 1,\ 2n+6, \tag{11}$$

TABLE 1 Design constraints

Description	Constraints
Flexural strength capacity, M_d	$M_d \ge M_u$
Shear strength capacity, V_d	$V_d \ge V_u$
The axial tension, T_d	$T = \phi A_s^{hoop} f_y \ge T_u$
Minimum steel ratio, ρ_{min}	$A_s \ge A_{smin}$
Maximum crack width, w_{max}	$w_{max} \le 0.1$ mm
Maximum steel bars spacing, S_{max}	$S \le S_{max}$
Minimum steel bars spacing, S_{min}	$S \ge S_{min}$
Minimum concrete cover, c_{cmin}	$c_{cmin} \ge 40$ mm

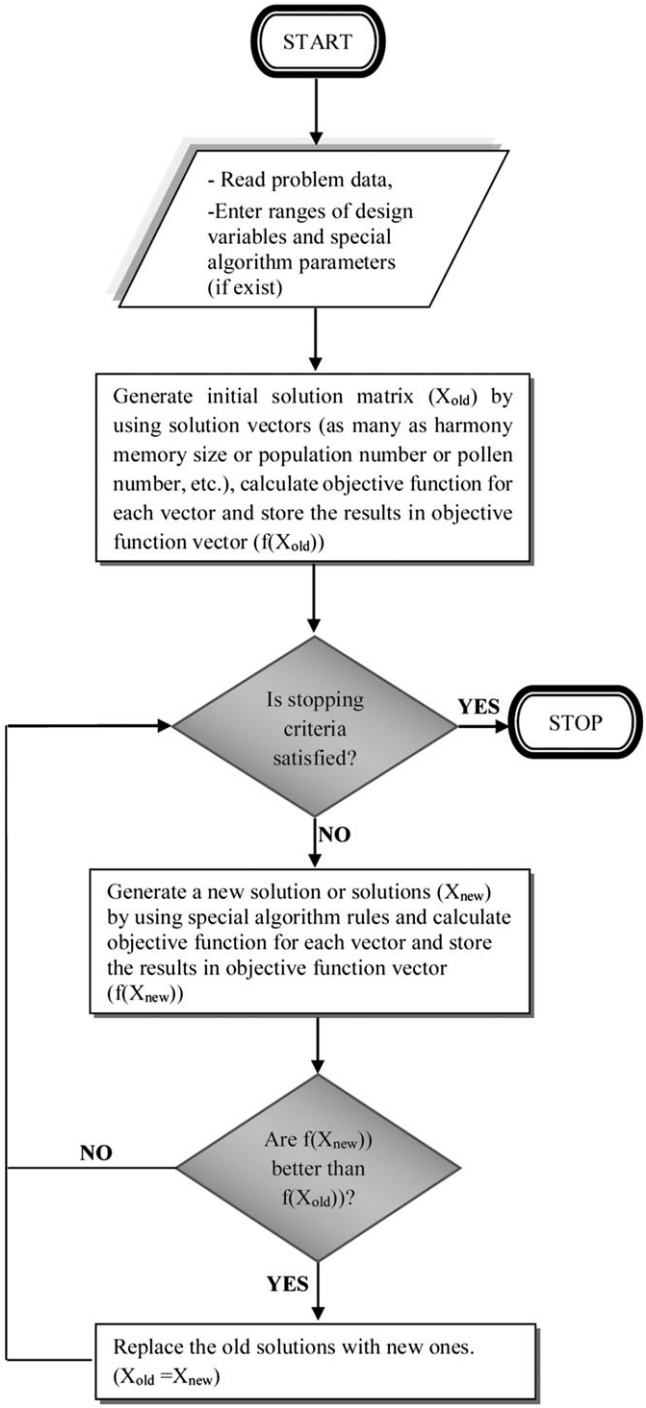

FIGURE 2 Flowchart of the program

in which rand(0, 1) represents a single uniformly distributed random number in the interval (0, 1). By repeating this process as many as the population number (pollen number for FPA, HMS for HS), the initial SM is obtained.

$$SM = \begin{bmatrix} X_{1,1} & X_{1,2} & \cdot & \cdot & \cdot & X_{1,2n+6} \\ X_{2,1} & X_{2,2} & \cdot & \cdot & \cdot & X_{2,2n+6} \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ X_{pn-1,1} & X_{pn-1,2} & \cdot & \cdot & \cdot & X_{pn-1,2n+6} \\ X_{pn,1} & X_{pn,2} & \cdot & \cdot & \cdot & X_{pn,2n+6} \end{bmatrix} \tag{12}$$

Each row of the SM represents a solution vector. As a final operation of this step, for all solution vectors, objective functions are calculated and stored in a vector, $f(X)$.

$$f(X) = \begin{bmatrix} f & (X_1) \\ f & (X_2) \\ \vdots & \\ f & (X_{pn-1}) \\ f & (X_{pn}) \end{bmatrix} \tag{13}$$

Step 3: In this step, stopping criteria (itermax) is checked. Steps 3–5 are consequently done until itermax value is satisfied.

Step 4: A new SM (or vector for HS algorithm) is generated by using special algorithm rules. As mentioned previously, this step is the unique process for algorithms. The mathematical operations are summarized in this section.

3.1 | HS algorithm

According to HS algorithm rules, only one solution vector is generated for each iteration. This vector can be constructed in two phases. In the first phase, design variables of new solution vector are generated by using whole solution domain (upper and lower limit) as it done in the second step (Equation (11)). In the second phase, a randomly selected vector (X_j) from the SM is used for generating new vector (Equation (14)).

$$X_{\text{new}} = X_j + (\text{rand}(0,1) - 0.5)\text{PAR}\left(X_i^{\max} - X_i^{\min}\right) \tag{14}$$

The HMCR is used for the decision of phase type for producing the new solution. This decision is done by comparing a random real number in the interval (0, 1) with HMCR value. If random number is smaller than the HMCR, the first phase, otherwise, the second phase is selected.

3.2 | Flower pollination algorithm

Despite creating one solution vector in the HS algorithm, FPA, TLBO, and JA algorithms create a new SM with similar dimensions (as many as pn number) to the initial SM. Similar to HS, there are two phases for the generation of new solutions in the FPA. In the first phase, the equation of generation of new SM (X_{new}) can be written as

$$X_{\text{new}} = X_{\text{old}} + L\left(X_{\text{old}} - g^*\right), \tag{15}$$

where g^*, L, and X_{old} are best solution, that is, solution vector with minimum objective function, $f(X)$, Lévy distribution, and existing solution in the SM. The expression of the second phase can be formulated as follows:

$$X_{\text{new}} = X_{\text{old}} + \text{rand}(0,1)(X_j - X_k), \tag{16}$$

in which X_j and X_k are values of two randomly chosen solutions from the existing ones. Like the HMCR in HS algorithm, a parameter called sp is used for the decision of selection for phase type.

3.3 | TLBO algorithm

Unlike selection of phase for production type done in the HS and FPA, two phases are sequentially applied in the TLBO algorithm. For that reason, two times more operations are done for each iteration step of TLBO. The mathematical formulations of these steps are

$$X_{\text{new}} = X_{\text{old}} + \text{rand}(0,1)\left(g^* - T_F X_{\text{mean}}\right) \tag{17}$$

and

$$X_{\text{new}} = \begin{cases} X_{\text{old}} + \text{rand}(0,1)(X_j - X_k); & f(X_j) > f(X_k) \\ X_{\text{old}} + \text{rand}(0,1)(X_k - X_j); & f(X_j) < f(X_k) \end{cases}, \tag{18}$$

where X_{mean} represents mean values of design variables and T_F is an integer number that formulated as

$$\text{T}_\text{F} = \text{round}[1 + \text{rand}(0,1)] \tag{19}$$

Equation (17) is the first phase called as teacher phase. The second phase formulized as Equation (18) is used in hybrid algorithms, and it is called as student phase.

3.4 | Jaya algorithm

Instead of two-phase algorithms, either selective or non-selective, the JA uses only a single phase that formulized as

$$X_{new} = X_{old} + \text{rand}(0,1)\left(g^{*} - |X_{old}|\right) - \text{rand}(0,1)(g^{w} - |X_{old}|), \tag{20}$$

in which g^{w} represents the solution vector with worst objective function among existing ones.

3.5 | Hybrid JAs

JA has no user-defined parameters and uses a single phase for production of new solutions. Although JA is effective in finding optimum results for problems given in Section 4, it may trap a local solution when the optimization process repeated several times. To overcome this situation, four different hybrid types of JA are developed and tested on the numerical examples.

In the first hybrid algorithm instead of linear random distribution of JA (Equation (20)), Lévy distribution simulating (L) flight of pollinators in FPA are used. This hybrid combination of JA and FPA is called JAL.

For the second hybrid algorithm, JAL and second phase of the TLBO algorithm (Equation (20)) are combined. Although JA considers combination of the best and worst solution in a single phase and ignoring the other candidate solutions of the matrix, in the second phase of TLBO, these solutions are considered by randomly choosing one of them. Due to having different strategies in single phase of JA and second phase of TLBO, it may be a good combination of these two phases for preventing local optima problem. These two phases are consequently applied in JALS2.

Application of two phases consequently may increase the number of analyses. For that reason, in the third hybrid algorithm, the sp of FPA is used to select either JA (Equation (20)) or student phase of TLBO (Equation (18)) in each iteration step. In the hybrid algorithm, sp value is assigned randomly by using rand(0, 1) function. Thus, there is no user-defined parameter in this hybrid algorithm. From origin, this single phase algorithm called as JAS.

As the fourth hybrid algorithm, differently from the third hybrid algorithm (JAS), instead of classical JA, JAL is used as a phase. The reason is that in third hybrid algorithm (JAS), using the equation of classical JA may not be good enough for overcoming local optima problem. This hybrid type algorithm is also a single phase, and it is called JALS.

Step 5: After the generation of new solutions, the objective functions of new, $f(X_{new})$, and existing, $f(X_{old})$ solutions are compared. If the new solution is better than existing one, the new ones are stored in place of existing ones.

4 | NUMERICAL EXAMPLES

The presented metaheuristic-based optimization methodologies were applied to two numerical examples with 12 cases (Table 2). The design constants and ranges of design variables are given in Table 3. In the optimization process, unit cost of concrete was \$40 for 20 MPa compressive strength of concrete, and unit costs were as +\$5 for every additional 5 MPa increase of compressive strength. For the long-term effect of post-tensioning cables, 26% strength loss is considered, and 70% of the tensile strength (f_{pu}) is taken for maximum allowable stress of cables. The upper limit of post-tensioning loads is related to the wall height (H) and liquid specific gravity (γ).

For the high number of design variables and a wide solution range, existing methods may not meet the needs of researchers in finding effective analysis results. For that reason, to guide researchers in future scientific studies, the effectiveness limits of existing algorithms are measured by changing wall height and number of post-tensioning forces in the cases (Table 2). At the same time, the performance of hybrid approaches is

TABLE 2 The cases for the optimization examples

Example no.	Case no.	Wall height	Number of post-tensioning loads	Number of design variables
1	1	4	1	8
	2	5	1	8
	3	6	1	8
	4	7	1	8
	5	8	1	8
	6	9	1	8
	7	10	1	8
2	8	10	5	16
	9	10	10	26
	10	10	15	36
	11	10	20	46
	12	10	25	56

TABLE 3 Design constants and ranges of design variables

	Definition	Symbol	Unit	Value
Design constants	Radius of wall	R	m	18.25
	Yield strength of steel	f_y	MPa	420
	Concrete cover	c_c	mm	40
	Max. aggregate diameter	D_{max}	mm	16
	Elasticity modulus of steel	E_s	GPa	200
	Elasticity modulus of concrete	E_c	MPa	4,700 $(f'_c)^{1/2}$
	Density of liquid	γ	kN/m^3	9.81
	Poisson ratio of concrete	v	—	0.15
	Tensile strength of post-tensioning cables	f_p	MPa	1,725
	Cost of concrete per m^3	C_c	$	40–65
	Cost of steel per ton	C_s	$	750
	Cost of post-tensioning cables per ton	C_p	$	2,900
	Workmanship cost	C_w	$/m^2	5
Ranges of design variables	Post-tensioning loads	P_t	kN/m	0–2γH
	Thickness at wall	t_w	m	0.2–2.0
	Compressive strength of concrete	f'_c	MPa	20–50
	Diameter of vertical reinforcing bars	ϕ_v	mm	8–50
	Diameter of horizontal reinforcing bars	ϕ_v	mm	8–50
	Distance between vertical reinforcing bars	S_v	mm	S_{min}[a] $\leq S_v \leq$ S_{max}[b]
	Distance between horizontal reinforcing bars	S_h	mm	S_{min}[a] $\leq S_h \leq$ S_{max}[b]

[a]S_{min} = max(25, ϕ).

[b]S_{max} = max(450, $5t_w$).

also compared with the existing methods. Regardless of the number of design variables, the novel hybrid approaches are generally effective on all examples. To determine the performance of the algorithms and hybrid methods, 30 independent runs proposed by Garcia et al.[46] are done, and frequently used statistical values for comparison of metaheuristic algorithms such as minimum, average, and standard deviation values with the number of analyses that obtained minimum value of wall are obtained.

The statistical values for Example 1 (Cases 1–7) are given in Table 4. According to the results, algorithms with best statistical values are different for cases. As seen in Table 4, the best algorithm in terms of all statistical values is clear for Cases 1 (TLBO), 2 (FPA), 4 (FPA), and 6 (JALS). But

TABLE 4 Optimum results for Example 1

		HS	FPA	TLBO	JA	JAL	JALS2	JAS	JALS
Case 1	Min. cost ($)	11,116	11,116	**11,116**	11,116	11,116	11,116	**11,116**	**11,116**
	Ave. cost ($)	11,116	11,116	**11,116**	11,380	11,116	11,116	**11,116**	**11,116**
	SD ($)	0	0	**0**	812	0	0	**0**	**0**
	Analyses num.	19,430	110	**20**	40	90	180	**50**	**60**
Case 2	Min. cost ($)	15,187	**15,181**	15,181	15,181	**15,181**	15,181	15,181	15,181
	Ave. cost ($)	15,243	**15,181**	15,232	15,551	**15,182**	15,182	15,443	15,181
	SD ($)	115	**0**	84	791	**1**	1	772	0
	Analyses num.	158,610	**84,570**	374,160	19,490	**179,040**	243,740	37,500	109,100
Case 3	Min. cost ($)	20,810	20,802	20,803	20,802	**20,802**	**20,802**	20,802	20,802
	Ave. cost ($)	20,917	20,824	20,838	20,991	**20,803**	**20,802**	21,074	20,802
	SD ($)	180	68	81	292	**1**	**0**	1,023	0
	Analyses num.	130,460	160,160	325,120	19,010	**185,240**	**271,940**	97,290	187,070
Case 4	Min. cost ($)	27,365	27,361	27,362	27,361	**27,361**	**27,361**	27,361	27,361
	Ave. cost ($)	27,389	27,361	27,385	27,602	**27,363**	**27,361**	27,409	27,361
	SD ($)	13	0	17	408	**1**	**0**	208	0
	Analyses num.	109,620	90,070	304,620	25,080	**114,080**	**160,220**	102,250	148,290
Case 5	Min. cost ($)	34,559	**34,545**	34,551	34,545	34,548	**34,545**	34,545	**34,545**
	Ave. cost ($)	34,591	**34,549**	34,571	34,670	34,555	**34,547**	34,736	**34,546**
	SD ($)	20	**11**	15	336	5	**5**	614	**2**
	Analyses num.	114,810	**158,850**	311,200	40,540	102,840	**272,540**	131,940	**174,090**
Case 6	Min. cost ($)	42,771	42,749	42,749	42,749	**42,749**	**42,749**	42,749	**42,749**
	Ave. cost ($)	42,820	42,752	42,765	43,047	**42,755**	**42,749**	42,818	**42,749**
	SD ($)	42	11	18	552	**4**	**0**	307	**0**
	Analyses num.	140,470	105,890	318,960	41,070	**129,460**	**186,440**	92,450	**124,330**
Case 7	Min. cost ($)	51,879	**51,849**	51,854	51,849	51,852	51,849	**51,849**	**51,849**
	Ave. cost ($)	51,933	**51,877**	519,21	52,212	51,865	51,945	**519,48**	**51,854**
	SD ($)	35	**32**	46	673	14	372	**371**	**9**
	Analyses num.	140,130	**181,530**	326,860	41,240	118,030	372,640	**165,820**	**198,880**

Note. FPA: flower pollination algorithm; HS: harmony search; JA: Jaya algorithm; JAL: Jaya algorithm using Lévy flights; JALS: Jaya algorithm using Lévy flights with probabilistic student phase; JALS2: Jaya algorithm using Lévy flights with consequent student phase; JAS: Jaya algorithm with probabilistic student phase; TLBO: teaching–learning-based optimization.

for the remaining ones, it may not be as easy as to determine the best algorithm because an algorithm can be good in a value and a different one may be better with the other value. For that reason, the best three algorithms have been identified and marked with bold characters in the table.

After this general evaluation, examining the results of the algorithms one by one in detail will be helpful in establishing an idea about the performance evaluation of each algorithm. According to the results, HS algorithm is not successful in finding optimum results except for the first case. Looking at the difference between the results obtained by the algorithm and the actual (best) results, it is seen that there are up to 0.58% and 0.55% differences for minimum and average costs values, respectively. In addition, in some cases, the standard deviation values are relatively high for HS. This may indicate that the algorithm is trapped to a local value. Especially in the analysis of the third case, when the standard deviation value and the number of analyses reaching to the optimum result (Optimum result is not changed after the approximately 65% of maximum analyses number [200,000].) are evaluated together for dedication of this probability becomes stronger.

Unlike the HS algorithm, FPA algorithm not only succeeded in finding the optimum result for all cases but also is among the algorithms that obtained the best optimum results (in Cases 2, 4, 5, and 7). The maximum difference between average cost value of FPA and best result is 0.1% for Case 3. When the standard deviations are considered, generally low values are obtained by the FPA. However, the standard deviations for Case 3 and especially Case 7 are relatively high values that it may mean that some of the independent runs trap at a local solution or the algorithm has difficulty to approach optimum solution. But when the results of these cases are evaluated collectively, the reason of high values more likely occurs because of approaching difficulty.

Before proceeding to the results of the other algorithms, the issues on selection algorithm parameters must be also mentioned. In the algorithms investigated in this study, parameter or parameters are only used in HS (HMCR and PAR) and FPA (sp). The other ones have no specific user-defined parameters that mean they are parameter-free algorithms. To show the effect of the user-selected parameters in optimum solution, the analyses of Case 7 were also done for different algorithm parameters of HS. The 3D plot of total cost versus HMCR versus PAR is shown in Figure 3. As seen from the plot, parameters have a significant effect on the analysis result, and the global search optimization of HS has limited effect on solutions.

The effect of the sp parameter of FPA on optimum solutions was also investigated in the same case. The changing of total costs to sp is given in Figure 4. As in the HS results, sp parameter has a significant effect on the analysis result of FPA, and the less use of global optimization (means sp < 0.5) than local one seems more suitable for finding the optimum result. From the parameter analyses of HS and FPA, it is seen that the selection of algorithm parameters that best fit for the problem is an important subject in itself and requires the user's experience.

When looked at TLBO results, it can be understood that the algorithm is only successful in finding the optimum results for Cases 1, 2, and 6 analyses. In the first case, despite being the best algorithm in terms of analysis number, the difference between the TLBO and other algorithms

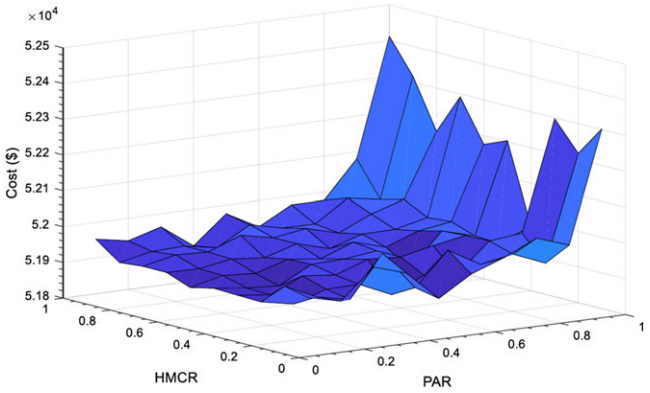

FIGURE 3 Cost versus harmony memory considering rate (HMCR) versus pitch adjusting rate (PAR) plot for Case 7

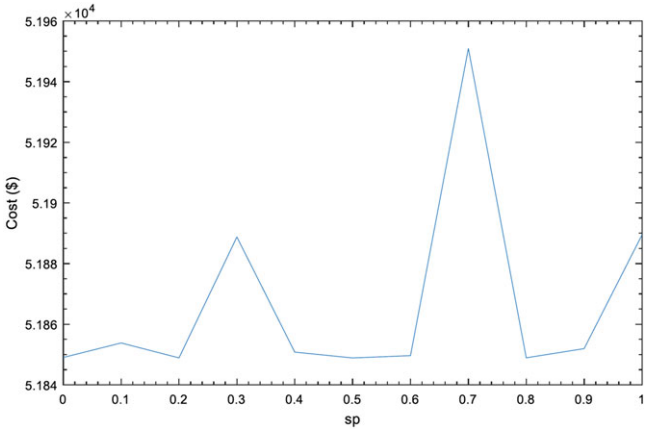

FIGURE 4 Cost versus switch probability (sp) plot for Case 7

(except HS) is not in a significant level. For cases that the algorithm could not find the optimum value, the maximum differences between TLBO and optimum result are 0.01% and 0.17% for minimum and average costs, respectively. Compared with the best values, the standard deviation values of the algorithm are generally high. When evaluating this result by also considering the ratio of analyses number that obtained optimum results and maximum iteration number (for the three highest cases are between 81% and 94%), it can be concluded that the algorithm may probably have a converging problem to the optimum value in some independent runs.

There are two significant conclusions, which are obtained from the JA results: the first one is that the algorithm succeeds to find optimum costs in all cases, and the second is the average costs and the standard deviations are very high. At the average costs, there are up to 2.44% (in Case 2) difference between JA and the best algorithm. Also, analyses number in which the optimum values are found seems quite low in some cases. When all these data are evaluated all together, it is understood that despite success in finding optimum result, most likely JA trapped a local optimum value in the process.

The newly proposed hybrid algorithms are developed to overcome local optima problem of the JA. To obtain best performance (not only best for statically values but also computational cost) for hybrid methods, four different hybridization techniques are considered. In the creation of hybrid algorithms, it is paid attention to providing the simple equation structure and non-parametric advantages of original form of JA also in hybrid ones.

According to the results, it is seen that the worst results are obtained by the JAS algorithm. Also, the tendency in the results (statistical values) of this algorithm is quite like the JA; that is, it succeeded in finding the optimum result but trapped to the local optimum values in some independent runs. For that reason, with the current performance, the JAS may not be the solution that sought for local optima problem of JA. Although the remaining three algorithms seem successful to obtain optimum result with relatively small statistical values, JALS algorithm comes to the forefront among the other hybrid methods. For example, JALS is not only successful in finding optimum value up to 40% less analyses number but also smaller standard deviation values are obtained (especially difference is quite high in Case 7). In addition, it must be noted that using Lévy flight instead of uniformly distributed random number, rand(0, 1), is the common point of these three algorithms. Therefore, it can be concluded that the Lévy flight may be one of the helpful operations to overcome the local optimum problem.

In Figure 5, the convergence plots for a run of Case 7 are presented. In this figure, HS is plotted differently, because the solution is updated after an analysis. For other population-based algorithms, the existing results are updated after all new solutions are provided for population. As seen from the figure, JA shows a good but sharp convergence behavior after the 5th iteration. This situation is good for rapid solutions, but it may cause to trap local optimum.

In the second example, the performances of the FPA, JAL, JALS2, and JALS algorithms, which were the best algorithms of the first example, are compared under more difficult cases. Because the other algorithms were not successful in relatively easy cases, these algorithms have not been performed in new ones. As seen in Table 5, in Example 2, five cases with design variables ranging from 16 to 56 are used. Even being more challenging, the highest wall of the first example (10 m), in other words, the largest range of design variables, is used in cases. Due to more challenging cases, the maximum number of analyses is increased to 400,000.

In Table 6, the analyses result for Example 2 (Cases 8–12) are given. As seen from the result, the best algorithms in terms of minimum costs are JALS2 for Cases 1 and 2, FPA for Case 3, and JALS for Cases 4 and 5. To present a more general overview for the performance of algorithms and the

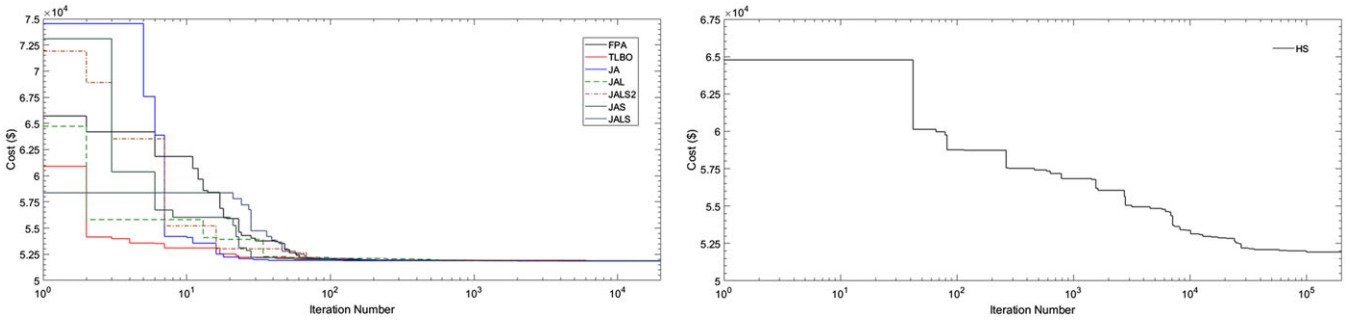

FIGURE 5 The convergence plot for Case 7. FPA: flower pollination algorithm; JA: Jaya algorithm; JAL: Jaya algorithm using Lévy flights; JALS: Jaya algorithm using Lévy flights with probabilistic student phase; JALS2: Jaya algorithm using Lévy flights with consequent student phase; JAS: Jaya algorithm with probabilistic student phase; TLBO: teaching–learning-based optimization

TABLE 5 The cases for the optimization Example 2

Case no.	Wall height	Number of post-tensioning loads	Number of design variables
8	10	5	16
9	10	10	26
10	10	15	36
11	10	20	46
12	10	25	56

results of the best and following algorithms are marked with bold. In this way, it can be found answer to the questions such as how suitable algorithms are and how far away from suitability. Thus, for the future studies, the researchers who are going to use the algorithm will be guided.

According to the results, the FPA algorithm only succeeded in finding the optimum result for Case 10. The maximum differences between FPA and the best algorithm are 5.91% for minimum and 6.03% for average costs, respectively. When the results of the algorithm are evaluated within itself, it is seen that there are up to 9.75% difference (Case 12) between minimum and average cost values. These results are also effective on the standard deviation values. Although these high values are first bringing the local optimum to mind, considering analyses number that obtained optimum results, it seems that there is a problem that can be overcome by increasing the maximum number of analyses. But for Case 12, the number of analyses indicates that for the some of the independent runs, the FPA algorithm has difficulties to approach optimum results.

Within the proposed hybrid methods, the only one that cannot find the optimum result in any case is the JAL algorithm. There are up to 7.40% difference between the optimum results of this algorithm and the best one. In addition, analyses numbers of the algorithm are between 72.80% and 40.65% of the maximum analyses number. This general tendency shows that the performance of the algorithm may not be sufficient in such cases with high design variables.

TABLE 6 Optimum results for Example 2

Case no.		FPA	JAL	JALS2	JALS
8	Min. cost ($)	49,748	50,903	**48,285**	**48,619**
	Ave. cost ($)	50,621	51,034	**50,612**	**50,403**
	SD ($)	367	118	**583**	**724**
	Analyses num.	388,910	285,420	**384,380**	**389,720**
9	Min. cost ($)	49,429	50,126	**46,671**	**47,424**
	Ave. cost ($)	50,494	50,946	**48,361**	**49,092**
	SD ($)	503	439	**1,456**	**1,357**
	Analyses num.	386,640	211,550	**390,110**	**395,290**
10	Min. cost ($)	**46,308**	47,968	**46,323**	46,345
	Ave. cost ($)	**50,238**	49,975	**48,804**	49,453
	SD ($)	**1,398**	911	**2,032**	1,818
	Analyses num.	**389,610**	162,740	**395,500**	395,660
11	Min. cost ($)	46,363	48,569	**46,013**	**45,646**
	Ave. cost ($)	50,266	49,989	**49,269**	**48,530**
	SD ($)	1,373	943	**2,474**	**2,193**
	Analyses num.	365,810	194,590	**396,850**	**394,530**
12	Min. cost ($)	**45,764**	47,528	46,198	**45,232**
	Ave. cost ($)	**50,224**	49,764	50,763	**47,366**
	SD ($)	**1,782**	915	2,634	**1,988**
	Analyses num.	**196,300**	291,210	396,240	**394,150**

Note. FPA: flower pollination algorithm; JAL: Jaya algorithm using Lévy flights; JALS: Jaya algorithm using Lévy flights with probabilistic student phase; JALS2: Jaya algorithm using Lévy flights with consequent student phase.

TABLE 7 Additional cases for comparison algorithms

Case no.	Wall height	Number of post-tensioning loads	Number of design variables
13	10	30	66
14	10	40	86
15	10	50	106

TABLE 8 Optimum results for Cases 13–15

Case no.		JALS2	JALS
13	Min. cost ($)	**45,558**	45,617
	Ave. cost ($)	**46,957**	48,262
	SD ($)	**2,268**	2,660
	Analyses num.	**995,162**	992,020
14	Min. cost ($)	**45,226**	45,291
	Ave. cost ($)	**48,473**	48,647
	SD ($)	**2,815**	2,297
	Analyses num.	**996,452**	986,640
15	Min. cost ($)	45,160	**44,572**
	Ave. cost ($)	47,908	**48,895**
	SD ($)	3,221	**2,652**
	Analyses num.	997,058	**997,700**

Note. JALS: Jaya algorithm using Lévy flights with probabilistic student phase; JALS2: Jaya algorithm using Lévy flights with consequent student phase.

Unlike JAL hybrid method, JALS2 and JALS algorithms have reached the optimum result in two cases. In other cases, the maximum difference between hybrid methods and the best algorithms are 2.14% for JALS2 and 1.61% for JALS, respectively. In the third case, where one of these two algorithms are not the best, JALS2 and JALS results are 0.03% and 0.08% bigger than best algorithm (FPA); that is, the differences are quite low levels. For that reason, there is no doubt about the performance of the algorithms. In terms of comparing algorithms, it can be useful to remind that in the FPA algorithm (the best algorithm for Case 10), this difference is around 6%.

5 | CONCLUSION

The numerical examples with 12 different cases are presented by increasing solution range and number for design variables. The hybrid methods were also considered if the original form of the algorithms has problems such as local optima problem, big computational time, and inappropriate statistical values.

The first example with one post-tensioning load has eight design variables. In seven different cases of this example, the effect of wall height on the performance of the algorithms is determined. In other words, the effect of the width of the boundaries of the solution set in which the optimum design variables are searched is investigated. For the first case with the smallest range, all algorithms are effective to find precise solution at independent runs. Except the HS algorithm, algorithms are reached to the optimum solution very quickly. In this case, the high analyses number of HS algorithm is an important result that should be emphasized in terms of performance. As it is expected, in the following cases, the HS algorithm could not find the optimum results. A similar situation is seen in the TLBO algorithm after the second case. Considering analyses results, the remaining algorithms can be evaluated in two separate groups.

The first group contains the JA and hybrid JAS. Although these algorithms are successful in finding the optimum result for each case, the other statistical values are relatively high compared with the second group. These high statistical values may indicate that in some analyses, these algorithms may have been trapped to a local optimum solution. This leads to an important question mark in terms of the performance of the algorithms in finding the optimum results precisely.

The second group consisted of the FPA, JAL, JALS2, and JALS. These algorithms are not only successful in finding optimum results but also have smaller statistical values; that is, algorithms have better performance in finding precise optimum results for each independent runs. This means that the algorithms are robust for the problem. Because the common point of the algorithms is to use Lévy distribution instead of uniformly distributed random number for randomizing, in future studies, it can be useful for researchers to use Lévy distribution when faced with local optima problem.

In the second example, the four best-performing (second group) algorithms in the first example have been tested in more difficult cases. Because one of the most challenging parameters to achieve the optimal result for the algorithms is the number of design variables, in this example, five different cases that number of design variables ranging from 16 to 56 were investigated. According to the results, except the single phase JAL hybrid method, each algorithm is succeeded in finding minimum value in one or two cases. In cases where algorithms cannot find the minimum result, a larger difference is obtained in the FPA algorithm than the other two algorithms.

In cases where the algorithm is not the best, differences between FPA and the best results are higher than the others. Additionally, in the case where the FPA algorithm is the best, the other two algorithms obtained almost the same results to the FPA. In this case, it can be said that the performance of the JALS2 and JALS algorithms is better than FPA.

The best algorithms such as JALS2 and JALS were tested for larger optimization problems having more than 56 design variables, which are shown in Table 7. In these analyses, the maximum number of analysis is one million to find the precise optimum. For these Cases (13–15), JALS2 is a little better in Cases 13 and 14 with 0.13% and 0.14% advantage (Table 8). For the last case with 106 design variables, JALS outperforms the JALS2 by 1.32% reduction on minimum cost.

As the conclusion of the investigation, although being effective and easy applied algorithm in point of no need to set any algorithm parameter, JA may trap a local optimum value due to its single formulation. By using the presented hybrid algorithms JAS2 or JALS, which also have no user-defined parameters, it can be overcome to the local optima problems for optimum design of post-tensioned cylindrical walls.

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