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Enhanced salp swarm algorithm based on opposition learning and merit function methods for optimum design of MTMD

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Abstract. Recently, population based optimization algorithms are developed to deal with a variety of optimization problems. In this paper, the salp swarm algorithm (SSA) is dramatically enhanced and a new algorithm is named Enhanced Salp Swarm Algorithm (ESSA) which is effectively utilized in optimization problems. To generate the ESSA, an opposition-based learning and merit function methods are added to standard SSA to enhance both exploration and exploitation abilities. To have a clear judgment about the performance of the ESSA, firstly, it is employed to solve some mathematical benchmark test functions. Next, it is exploited to deal with engineering problems such as optimally designing the benchmark buildings equipped with multiple tuned mass damper (MTMD) under earthquake excitation. By comparing the obtained results with those obtained from other algorithms, it can be concluded that the proposed new ESSA algorithm not only provides very competitive results, but also it can be successfully applied to the optimal design of the MTMD.

Keywords: salp swarm algorithm; enhanced SSA; opposition based learning; merit function; optimization; multiple tuned mass damper

1. Introduction

The main concern of civil engineering is to diminish undesired vibrations of the structures caused by lateral excitations such as wind and earthquake. Different theories and methods have been proposed and directed to overcome this concern over the years. One of these methods is to implement the control devices, which enhance the structural performance against vibration excitations and diminish the structural dynamic responses (Ghaffarzadeh and Younespour 2014, Saaed *et al*. 2015). The control devices can be categorized into either, passive, semi-active, active or hybrid control systems (Fisco and Adeli 2011a, Fisco and Adeli 2011b, Younespour and Ghaffarzadeh 2015, Han *et al*. 2019, Azar *et al*. 2020b, Aghabalaei *et al*. 2019). Among these systems, TMD, which is a passive device, is the most popular and reliable one due to different reasons such as its simple formulation and its successful applications in real life (Chey and Kim 2012). TMD is consisted of a mass, a spring and a damper, which is usually installed on the upper floors of the building to diminish the structural vibrations.

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By tuning the frequency of the damper to a specific structural frequency, the damper starts to resonate out of phase with the structural motion when that specific frequency is excited. Therefore, the damper inertia force reacting to the building will dissipate the energy.

It is clear that by defining the optimum mechanical parameters such as the optimum tuning frequency, damping and mass ratio of TMD, the efficiency of the control device will be improved. It means that a key point to design a TMD to mitigate dynamic responses of a structure is to determine its optimal parameters. Intensive researches worked on TMD have been focused on finding optimum parameters and evaluating the efficiency of the system under various dynamic actions.

On the other hand, many new natural evolutionary algorithms have been developed with the purpose of solving different engineering problems, such as imperialist competitive algorithm (ICA) (Ghaffarzadeh and Raeisi 2016), charged system search (CSS) (Kaveh and Talatahari 2010), grey wolf optimizer (GWO) (Mirjalili *et al*. 2014, Azar *et al*. 2020a), grasshopper optimization algorithm (GOA) (Arora and Anand 2019, Raeesi *et al*. 2020), salp swarm algorithm (SSA) (Mirjalili *et al*. 2017) and so on. In this paper SSA, one of the recent swarm optimization algorithms, is selected as an optimization algorithm. SSA proved its superiority and outperformance in comparison with other well-known optimization algorithms over several types of problems. In addition, SSA has special characteristics such as simplicity and flexibility. However, SSA, like other optimization algorithms suffers from some problems such as population diversity and local optima. To overcome these problems, two methods such as opposition-based learning (OBL) and merit function (MF) are added to standard SSA.

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There are many literatures exist in which OBL is used to improve different optimization algorithms which can be treated as a proof that using OBL can boost the performance of the algorithms. For example, Sarkhel *et al*. (2017) applied OBL to the Harmony Search (HS) to improve its convergence speed. Shan *et al*. (2016) used OBL to improve the population diversity and convergence speed of the Bat Algorithm (BA). Sapre and Mini (2019) utilized OBL to enhance the convergence rate of the moth flame optimization (MFO). Zhou *et al*. (2017) used OBL to improve the convergence speed and population diversity of the memetic algorithm (MA). In this paper, OBL is added to SSA to enhance the exploration and convergence rate. Moreover, to enhance the exploitation ability, MF is also added to SSA. In contrast with OBL, which is used in the majority of optimization algorithms, MF is rarely found in optimization algorithms. The concept of the MF is mostly used in reliability analyses to better converge to the design point (Hadidi *et al*. 2019, Der Kiureghian *et al*. 1994). This function is used to efficiently balance exploration and exploitation. In other words, it decreases the searching tendency nearby the best location with more iterations.

Recently, the application of the optimization algorithm in the optimum design of the tuned mass damper has been focused by the control device researchers (Salvi and Rizzi 2017, Salvi and Rizzi 2015). Utilizing the GA to get the optimized parameters of the TMD was proposed by Hadi and Arfiadi (1998). They employed the H2 norm of the transfer function from the external disturbance to a regulated output as a performance measure of the optimization criterion. Lee *et al*. (2006) suggested a numerical method to estimate the optimum parameters of TMD. In their study, by minimizing a performance index of the structural responses defined in the frequency domain, the optimal parameters of the damping coefficient and spring constant are determined for the TMD. Bekdaş and Nigdeli (2011) utilized harmony search (HS) algorithm to find optimum parameters of TMD. In their study, the objective function which is optimized by HS is based on the peak values of first story displacement and acceleration transfer function. The result of their work showed outstanding reduction in structural responses, however, these results are yet under discussion (Bekdaş and Nigdeli 2013, Fadel Miguel *et al*. 2013). Applying CSS algorithm to estimate optimum parameters of TMD was proposed by Kaveh *et al*. (2015). They assumed the maximum values of the first story displacement with and without TMD, and the transfer function from input ground acceleration to the first story acceleration response as an optimization criteria.

As mentioned above, TMD can suppress structural vibrations when its frequency is tuned to a specific structural frequency, but if excited frequency deviates from the structural frequency or TMD's frequency, its control effect can be significantly reduced and even the structural response may be intensified. To overcome this problem, the concept of multiple tuned mass dampers (MTMDs) with frequencies tuned in the neighborhood of the natural frequency of an SDOF primary system to improve the performance of the TMD system was proposed by Xu and Igusa (1992). After that, numerous studies have been presented based on the behavior of MTMDs. Setareh (1994) proposed a doubly tuned mass damper (DTMD), which is consisted of two masses connected in series to the structure. Several MTMD models with different combinations of restrictions on MTMD physical or modal parameters were presented by Li (2002) and Li and Liu (2003). Rana and Soong (1998) investigated the effect of TMD and MTMD to control a particular structural mode and also to control a multi-degree-of-freedom (MDOF) structure, respectively. Li and Qu (2006) worked on the effect of changing the mass of MTMD in translational and torsional response reduction. In their study, a simplified two-degree-of-freedom (2DOF) structure with identical stiffness and damping coefficient for MTMD is considered. Also, their study had the capability of representing the dynamic characteristics of general asymmetric structures excited by earthquakes.

This paper can be categorized into two main points of view. From the first point of view, the newly developed optimization algorithm (SSA) is selected as an optimization algorithm. To enhance the exploration and exploitation abilities of this algorithm, two methods such as opposition-based learning (OBL) and merit function (MF) are added to the standard SSA and enhanced its performance (ESSA) in dealing with some mathematical benchmark test functions.

From second point of view, the new ESSA algorithm is applied to the engineering problem. MTMD as a passive and reliable control device is selected to control the dynamic response of the structures. As it is important to design this control device correctly to achieve its best performance, ESSA is utilized to optimally design the MTMD. To investigate the performance of the optimum MTMD, two benchmark buildings are selected and their results are compared with some other papers.

2. Optimization algorithm

2.1 Standard Salp Swarm Algorithm (SSA)

In 2017, Mirjalili *et al*. (2017) proposed a new meta-heuristic algorithm which is inspired from the swarming behavior of the salps. Their movement and also tissues are so similar to jellyfishes. The main features of this type of animals are their ability to form a chain and searching for optimal locomotion based on rapid foraging and coordinated changes. The salp chain is divided into two categories: leader and followers. The leader is the salp at the front of the chain, however the rest of the salps are known as followers. The swarm is guided by the leader, while the followers follow each other. By defining the y as the position of a salp and denoting the F as the food source which is the target of the swarm in the search space, the position of the leader is updated using the following equation

$$y_j^i = \begin{cases} F_j + r_1((ub_j - lb_j)r_2 + lb_j), & r_3 \geq 0 \\ F_j - r_1((ub_j - lb_j)r_2 + lb_j), & r_3 < 0 \end{cases} \tag{1}$$

where y_j^i denotes as the leading salp's position in the jth dimension. lb_j and ub_j are the lower boundary and upper boundary, respectively. r_2 and r_3 are randomly generated numbers. The coefficient r_1 is responsible for balancing between exploitation and exploration, and it is defined as follows

$$r_1 = 2e^{-\left(\frac{4t}{T}\right)^2} \tag{2}$$

where t is the current iteration number, and T is the maximum number of iterations. By considering the Newton's law of motion, the followers update their position according to the following equation

$$y_j^i = \frac{1}{2}\alpha l^2 + \beta_0 l \tag{3}$$

where y_j^i shows the position of ith follower in jth dimension ($i \geq 2$), β_0 is the initial speed, $\alpha = \frac{\beta_{final}}{\beta_0}$, $\beta = \frac{y-y_0}{t}$ and l is time. As the time is called an iteration in the optimization process, the discrepancy within iteration equals to one. By assuming the $\beta_0 = 0$, the updating position of followers in jth dimension can be represented as follows

$$y_j^i = \frac{1}{2}(y_j^i + y_j^{i-1}) \tag{4}$$

2.2 Opposition-based learning

The opposition-based learning (OBL) method is firstly introduced by Tizhoosh (2005) for machine intelligence and it is based on proposing an opposite numtber. It means that an opposite solution is generated based on the current solution and the upper and lower bounds of a range. For example, the opposite of the real number h which is bounded between a and b ($h \in [a, b]$) can be obtained using the following equation.

$$\bar{h} = b + a - h \tag{5}$$

To extend this definition into n–dimensions the following equation is used:

$$\bar{h}_i = b_i + a_i - h_i, \qquad i = 1, 2, \ldots, N \tag{6}$$

where $\bar{h} \in R^n$ is the opposite vector from the real vector $h \in R^n$. Moreover, the best solution will be stored after comparing the two solutions (h and $\bar{h}$). Thus, the other one will be eliminated by comparing the fitness function. For example, if $f(h) \leq f(\bar{h})$ (for maximization), then $\bar{h}$ will be saved and h will be eliminated.

Recently, OBL has attracted considerable attention due to its ability to increase the convergence rate of an optimization algorithm. For more clarification, it doubles the population in each iteration which leads to achieve a better population. Among the newly generated initial population in every iteration, the better ones (half of the newly generated population) are stored and the others are deleted. This feature enhances the convergence rate of the optimization algorithm.

2.3 Merit function

The merit function (MF) is based on the concept which is mostly used in reliability analyses to better converge to the design point (Hadidi *et al*. 2019; Der Kiureghian *et al*. 1994; Shirgir *et al*. 2020). The aim of utilizing the MF in the optimization problems is to improve the exploitation properties such as increasing the convergence rate and decreasing the cost function. The MF should have a global minimum at the solution point of X_i' and it should decrease in each iteration step. The step size s' is assumed to be set by the following equation.

$$s'_{i+1} = \begin{cases} \frac{m(X'_{i-1})}{m(X'_i)} s'_i & m(X'_i) \geq m(X'_{i-1}) \\ s'_i & m(X'_i) < m(X'_{i-1}) \end{cases} \tag{7}$$

where $m(X_i')$ is the MF and can be calculated according to the Eq. (8)

$$m(X_i') = \left\| X_i' - \frac{\nabla^T g(X_i') X_i'}{\nabla^T g(X_i') \nabla g(X_i')} \nabla g(X_i') \right\|^2 + \frac{g(X_i')^2}{g(X_0')^2} \tag{8}$$

in which $\nabla g(X_i')$ is the gradient vector of the cost function $g(X_i')$ at point X_i', and X_0' is the initial random point. Obviously, the MF is a positive value which can be calculated according to the former results of the objective function $m(X_i') \geq 0$. Also, the initial step size is assumed to be 1 (i.e $s'_0 = 1$). According to the above adaptive step size in Eq. (7), it is clear that $s'_{i+1} \leq s'_i$.

2.4 Proposed Enhanced Salp Swarm Algorithm (ESSA)

In this section, an opposition-based learning (OBL) and merit function (MF) based salp swarm algorithm (SSA) is proposed, where OBL and MF are both added to the SSA to enhance its performance. One of the parameters which affect the performance of the SSA is the r_1 parameter, which balances between exploitation and exploration. Exploration concentrates on finding better new solutions by

```
Generate random values for initial salps positions  y_j^i
Set the current iteration  it = 1
while (it < maximum number of iterations) do
    Compute the cost function
    Find the best solution F
    Calculate the gradient of the cost function for each
    salp
    Compute the MF and step size (s') by Eq. (7)
      for each salp
        if (i==1)
        Update the position of the leading salp by Eq. (1)
        else
        Update the position of the follower salp by Eq. (4)
        end
      end for
  Determine the opposition of the salps (y'_j^i) by Eq. (6)
  Update the positions
  it=it+1
  end while
return F.
```

Fig. 1 Pseudo-code for the Enhanced Salp Swarm Algorithm (ESSA)

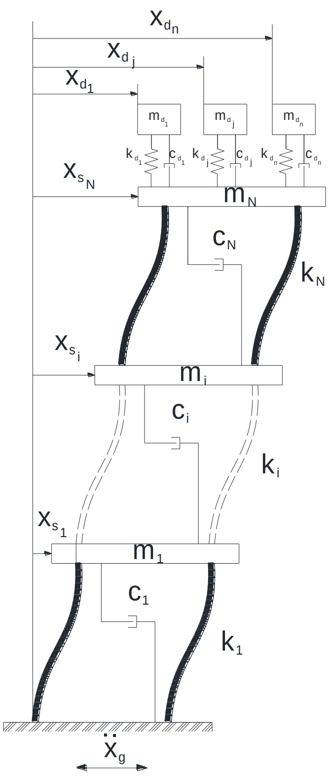

Fig. 2 N-story shear building structure equipped with MTMD on top floor under earthquake excitation

investigating the search space on a large scale, while exploitation concentrates on exploiting the data in the local region. In this paper, the r_1 parameter is replaced by the step size s' (Eq. (7)) to handle the exploitation and exploration abilities of the SSA. Also, OBL is added to SSA to enhance the exploration phase and to reach the optimal value quickly and repair the out-of-range values. The pseudo-code for the ESSA is given in Fig. 1.

3. Outline for the optimum design of the MTMD

To better understand how the proposed new ESSA performs in dealing with designing control devices, at first, it is needed to explain the governing equation of the structure equipped with control devices. In the following subsection, the equation of motion for the structure equipped with MTMD is presented. Also, in the next subsection, the procedure of utilizing the proposed ESSA in finding optimum MTMD parameters will be described.

3.1 Equations of motion

The equation governing dynamic response of the N-story shear building structure equipped with MTMD on top floor and excited with earthquake which is depicted in Fig. 2, is formulated as

$$M\ddot{X}(t) + C\dot{X}(t) + KX(t) = -ME\ddot{X}_g \tag{9}$$

where X is the displacement vector which consists of the displacements of the N-story shear building structure, x_{s_N} (N=1,..,N), and the displacements of the n TMDs, x_{d_n} (n=1,…,n). That is

$$X = [x_{s_1}\ x_{s_2}\ x_{s_3} \dots x_{s_N}\ x_{d_1}\ x_{d_2} \dots x_{d_n}]^T \tag{10}$$

In Eq. (9), M, C, and K represent mass, damping, and stiffness matrices, respectively with following forms (Eqs. (11-13)

$$M = diag[m_1\ m_2\ m_3 \dots m_N\ m_{d_1}\ \dots\ m_{d_n}] \tag{11}$$

where m_i, c_i, k_i and x_{s_i} are mass, damping coefficient, stiffness and displacement of ith story of building (i = 1, 2, . . . , N). m_{d_i}, c_{d_i}, k_{d_i} and x_{d_i} are mass, damping coefficient, stiffness and displacement of ith TMD with respect to the ground which is installed on top of the building as can be seen in Fig. 2.

Solving Eq. (9) directly is not an easy task, so by transforming coupled dynamic equations into uncoupled form, it can be easily solved for each mode. The final form of uncoupled dynamic equation of motion can be seen in Eq. (14) or alternatively in Eq. (15).

$$C = \begin{bmatrix} (c_1+c_2) & -c_2 & 0 & & & & \\ -c_2 & (c_2+c_3) & -c_3 & & \cdots & & \\ 0 & -c_3 & \ddots & & & & \\ & & & (c_N + \sum_{i=1}^{n} c_{d_i}) & -c_{d_1} & \cdots & -c_{d_n} \\ & \vdots & & -c_{d_1} & c_{d_1} & & \\ & & & \vdots & & \ddots & \\ & & & -c_{d_n} & & & c_{d_n} \end{bmatrix}_{(N+n)\times(N+n)} \tag{12}$$

$$K = \begin{bmatrix} (k_1+k_2) & -k_2 & 0 & & & & \\ -k_2 & (k_2+k_3) & -k_3 & & \cdots & & \\ 0 & -k_3 & \ddots & & & & \\ & & & (k_N + \sum_{i=1}^{n} k_{d_i}) & -k_{d_1} & \cdots & -k_{d_n} \\ & \vdots & & -k_{d_1} & k_{d_1} & & \\ & & & \vdots & & \ddots & \\ & & & -k_{d_n} & & & k_{d_n} \end{bmatrix}_{(N+n)\times(N+n)} \tag{13}$$

$$M_i\ddot{Y}_i(t) + C_i\dot{Y}_i(t) + K_iY_i(t) = -\mathbf{M}\{\mathbf{1}\}\ddot{x}_g(t) \tag{14}$$

$$\ddot{Y}_i(t) + 2\zeta_i\omega_i\dot{Y}_i(t) + \omega_i^2Y_i(t) = \frac{-\mathbf{M}\{\mathbf{1}\}\ddot{x}_g(t)}{M_i} \tag{15}$$

in which M_i, C_i,K_i, Y_i, $\omega_i$and ζ_i are generalized mass, damping, stiffness, displacement, natural frequency and damping ratio of the ith normal mode, respectively.

3.2 ESSA for MTMD parameters optimization

To obtain the optimum parameters of MTMD such as mass, damping, and stiffness, the salp swarm algorithm is selected and enhanced (ESSA) and utilized. To reach this goal, at first a building without MTMD is modeled in MATLAB R2014a program to get its dynamic response such as displacements of different floors. For this purpose, the Newmark average acceleration method (c = 1/2 and b = 1/4) was employed to solve the uncoupled form of the dynamic equation of motion (Eq. (15)). In the next step the building in which MTMD are implemented on the top floor is modeled and their parameters such as mass, damping and stiffness are adjusted by ESSA. It searches random TMD parameters around upper and lower bound values in each

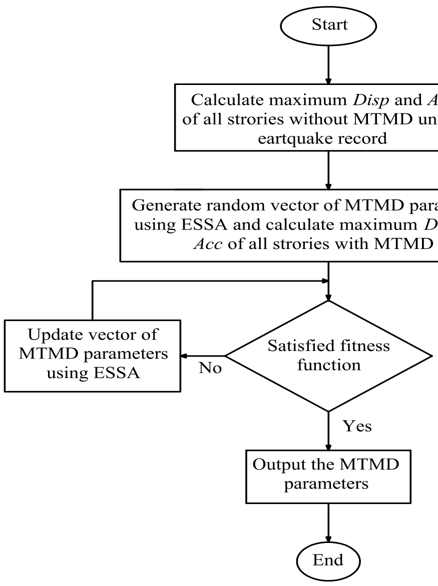

Fig. 3 Flowchart for the optimum design of the MTMD using ESSA

iteration. All results are checked until the objective function is satisfied. If the objective function is not satisfied, a new vector must be generated. The objective function which is used in this paper is the minimization of the maximum displacement and acceleration of the all story with and without MTMD as following:

$$Objective\ function = \frac{\sum_{i=1}^{n} |\max(x_i)|_{controlled}}{\sum_{i=1}^{n} |\max(x_i)|_{uncontrolled}} + \frac{\sum_{i=1}^{n} |\max(\ddot{x}_i)|_{controlled}}{\sum_{i=1}^{n} |\max(\ddot{x}_i)|_{uncontrolled}} \quad (16)$$

where n represents the number of stories. Also, x_i and $\ddot{x}_i$ are the ith story's displacement and acceleration, respectively. The flowchart of the proposed method is illustrated in Fig. 3.

4. Numerical examples

In the following subsections, ESSA is applied to two kinds of problems. At first, some mathematical benchmark test functions are selected to examine the efficiency of the new algorithm. Next, to generalize the ESSA in dealing with engineering problems, an optimum design for the benchmark buildings equipped with MTMD is tested.

4.1 Verifying ESSA using mathematical test functions

To compare the performance of ESSA with original SSA, eight benchmark test functions are selected in which the first four functions are related to uni-modal test functions and others are related to muti-modal test function. It is worth mentioning that, the multimodal test functions, in contrast with uni-modal ones, have more than one optimum value, and therefore the exploration ability of the algorithms to avoid trapping in local optima can be examined. The uni-modal and multi-modal mathematical descriptions are presented in Table 1 and their 3-D graphs are all depicted in Fig. 4. It should be noted that the dimension of the search space for all of the test functions is equal to 10. To have a fair judgment, the number of search agents and the maximum number of iterations are assumed to be as 40 and 600, respectively. After running the program for 25 times for independent tests for each algorithm, the comparison results are summarized in Table 2. As can be seen from Table 2, the original SSA optimization somehow fails to find the minimum of the functions, however, the ESSA can find the optimum values, better than its original one. Moreover, to make the results much more understandable, convergence history of the test functions for the SSA and ESSA are all illustrated in Fig. 5.

4.2 Verifying ESSA using engineering problem

In this subsection, to check the efficiency of the proposed optimization algorithm in handling the engineering problems, two benchmark buildings (Hadi and Arfiadi 1998, Lee *et al.* 2006, Bekdaş and Nigdeli 2011, Kaveh *et al.* 2015) are selected. In these examples, ESSA is applied to find the optimum parameters of the MTMDs for dynamic response reduction. For the both following examples, the parameters used in the ESSA including number of population size and maximum number of iteration are taken as 35 and 300 respectively.

4.2.1 Example 1

A ten-story shear building (Hadi and Arfiadi 1998, Lee *et al.* 2006, Bekdaş and Nigdeli 2011, Kaveh *et al.* 2015) with uniform properties for all stories in which MTMD is installed on the top floor is selected as a first engineering example. For this example, the structural properties such as elastic stiffness, mass, and linear viscous damping coefficient are considered as k= 650 MN/m, 360 tons and 6.2 MN s/m, respectively. To examine the effectiveness of the proposed optimization algorithm (ESSA), three cases of using TMDs which including two, four and six-TMDs are considered. The lower and upper bounds for TMD parameters for each case are indicated in Table 3.

It should be mentioned about Table 3 that, the total mass of TMDs in different cases for upper bound are equal to 60 ton. The convergence histories for all three cases using both ESSA and standard SSA under El-Centro 1940 NS excitation, regarding the objective function in Eq. (16), is depicted in Fig. 6.

4.2.2 Example 2

To investigate the efficiency of the ESSA, another 10-story building which is investigated by different researchers (Den Hartog 1985, Hadi and Arfiadi 1998, Bekdaş and Nigdeli 2011, Warburton 1982, Sadek *et al.* 1997, Kaveh *et al.* 2015) with each floor's property as Table 6, is selected. In this example, the damping matrix is assumed to be $\boldsymbol{C} = 0.0129\boldsymbol{K}$ and also the first mode of building is considered. By assuming the same conditions of Example 1 for

Table 1 Benchmark test functions

Function	*Dim*	*Range*	f_{min}
Unimodal			
$f_1(x)=\sum_{i=1}^{n} x_i^2$	10	[-100,100]	0
$f_2(x)=\sum_{i=1}^{n}\lvert x_i\rvert+\prod_{i=1}^{n}\lvert x_i\rvert$	10	[-10,10]	0
$f_3(x)=\sum_{i=1}^{n}\left(\sum_{j-1}^{i} x_j\right)^2$	10	[-100,100]	0
$f_4(x)=\max_i\{\lvert x_i\rvert,\quad 1\le i\le n\}$	10	[-100,100]	0
Multimodal			
$f_5(x)=\sum_{i=1}^{n}\left[x_i^2-10\,cos(2\pi x_i)+10\right]$	10	[-5.12,5.12]	0
$f_6(x)=20\left(1-e^{-0.2\sqrt{0.5(x^2+y^2)}}\right)-e^{0.5(cos(2\pi x)+\cos(2\pi y))}+e$	10	[-32,32]	0
$f_7(x)=1+\frac{1}{4000}\sum_{i=1}^{n} x_i^2-\prod_{i=1}^{n}\cos\left(\frac{x_i}{\sqrt{i}}\right)$	10	[-600,600]	0
$f_8(x)=0.1\left\{sin^2(3\pi x_1)+\sum_{i=1}^{n}(x_i-1)^2[1+sin^2(3\pi x_i+1)]+(x_n-1)^2[1+sin^2(2\pi x_n)]\right\}+\sum_{i=1}^{n}u(x_i,5100,4)$	10	[-50,50]	0

Table 2 Performance of the SSA and ESSA dealing with mathematical test functions

Function	Algorithm	Best	Worst	Mean	Standard deviation
$f_1(x)$	SSA	9.1254e-11	4.9835e-10	3.2390e-10	1.2016e-10
	ESSA	**2.1805e-18**	2.848e-15	1.291e-16	1.975e-17
$f_2(x)$	SSA	2.4118e-06	6.9724e-06	5.0412e-06	1.1500e-06
	ESSA	**8.3657e-10**	4.9143e-07	1.7595e-09	5.7539e-08
$f_3(x)$	SSA	1.3195e-10	7.7713e-09	1.9703e-09	1.7439e-09
	ESSA	**2.0409e-15**	5.4951e-13	2.1897e-14	9.3223e-14
$f_4(x)$	SSA	5.7923e-06	1.7733e-04	1.2112e-05	2.7079e-06
	ESSA	**5.5391e-09**	6.2547e-07	6.5640e-08	1.9754e-09
$f_5(x)$	SSA	4.7049e-12	1.0023e-10	3.6184e-11	6.1637e-11
	ESSA	**6.8369e-18**	3.5474e-14	7.3182e-16	4.5427e-17
$f_6(x)$	SSA	4.5956e-06	9.4020e-06	7.1905e-06	1.3411e-06
	ESSA	**5.2879e-10**	4.6295e-07	1.4873e-09	2.7930e-10
$f_7(x)$	SSA	1.0623e-07	1.002e-05	3.618e-06	6.163e-05
	ESSA	**7.8648e-12**	2.6832e-10	3.9053e-11	6.1930e-11
$f_8(x)$	SSA	8.4688e-12	1.2798e-10	2.5814e-11	4.4547e-10
	ESSA	**7.3105e-17**	4.9825e-14	4.3445e-15	8.4893e-16

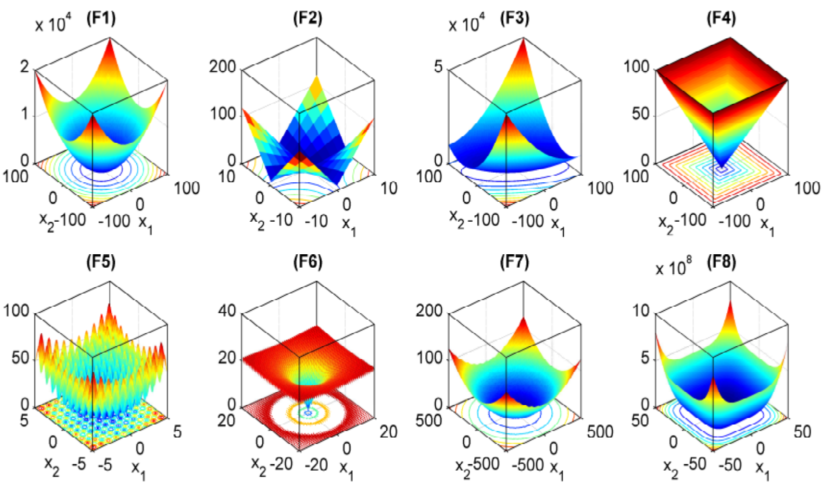

Fig. 4 The 3-D graphs for the benchmark test functions

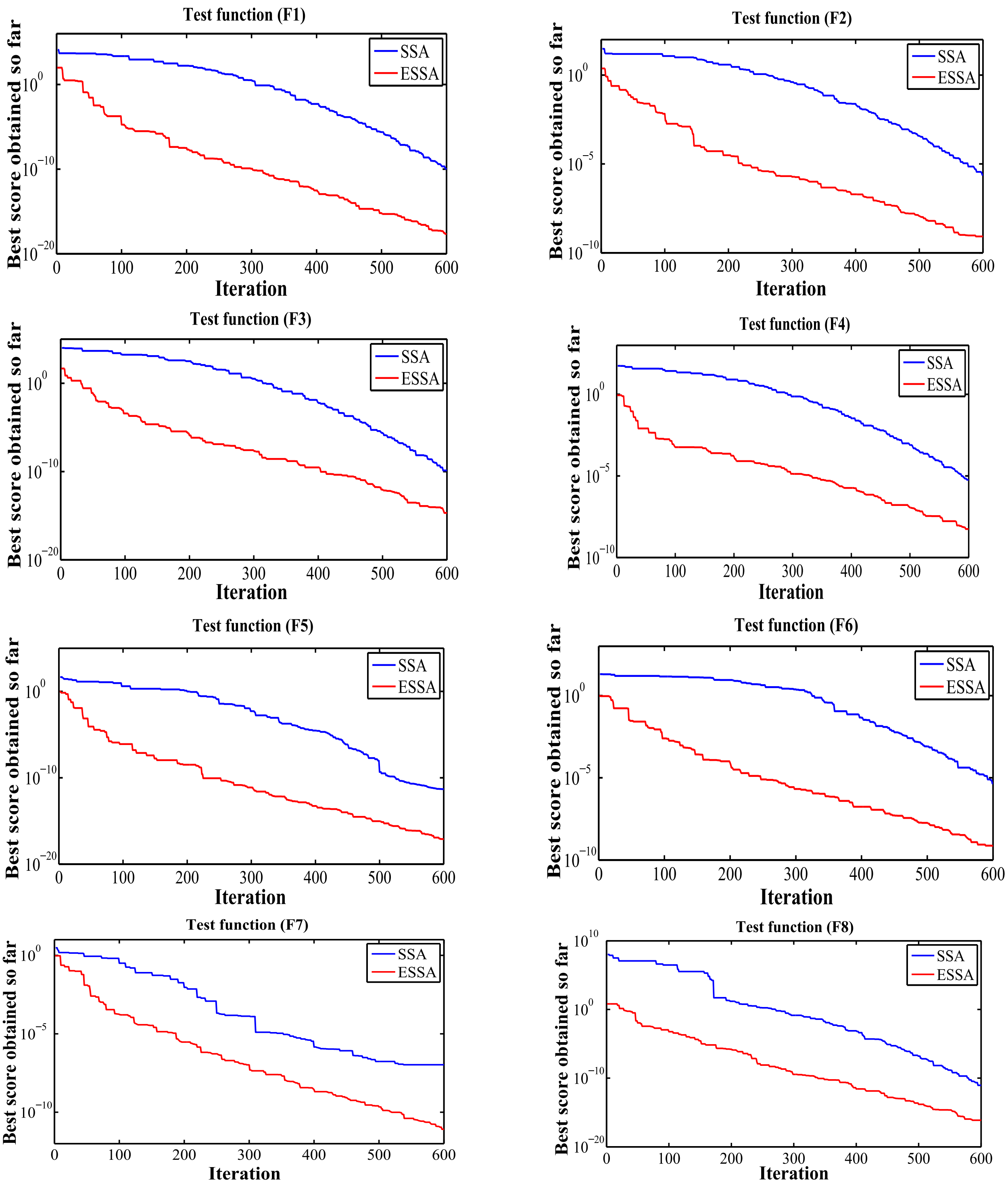

Fig. 5 Convergence history of the test functions using the SSA and ESSA

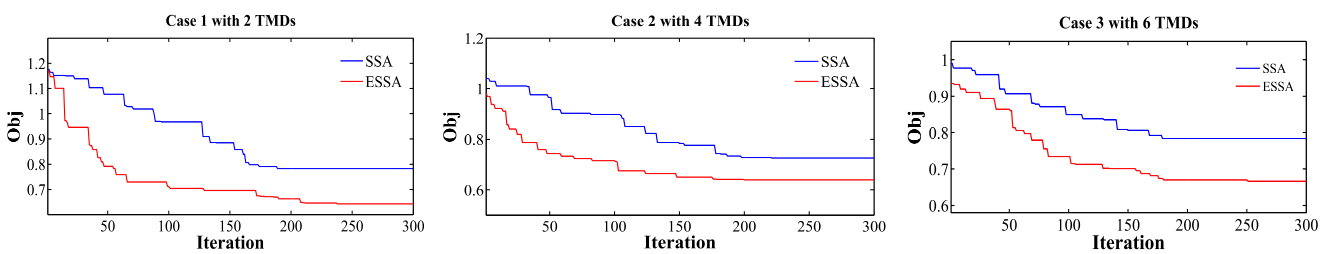

Fig. 6 Convergence histories using ESSA and SSA for optimum parameter design of MTMD in 3 cases

Table 3 Upper and lower bounds for each TMD parameters

	m_d			c_d	k_d
Number of TMDs	Case 1 (n=2)	Case 2 (n=4)	Case 3 (n=6)	n=2,4,6	n=2,4,6
Lower bound	3	3	3	0.01	0.5
Upper bound	30	15	10	0.3	3.5

Table 4 Optimum MTMD parameters obtained from ESSA

	Case 1 (n=2)		Case 2 (n=4)				Case 3 (n=6)					
$m_d(t)$	13.18	15.78	10.05	12.73	11.13	5	10	5.29	5.69	8.77	10	5.48
$c_d\ (MN\frac{s}{m})$	0.29	0.01	0.01	0.3	0.28	0.27	0.3	0.12	0.095	0.09	0.3	0.05
$k_d\ (\frac{MN}{m})$	0.52	1.04	2.67	0.5	0.5	1.79	0.5	2.96	2.06	1.87	0.5	1.40

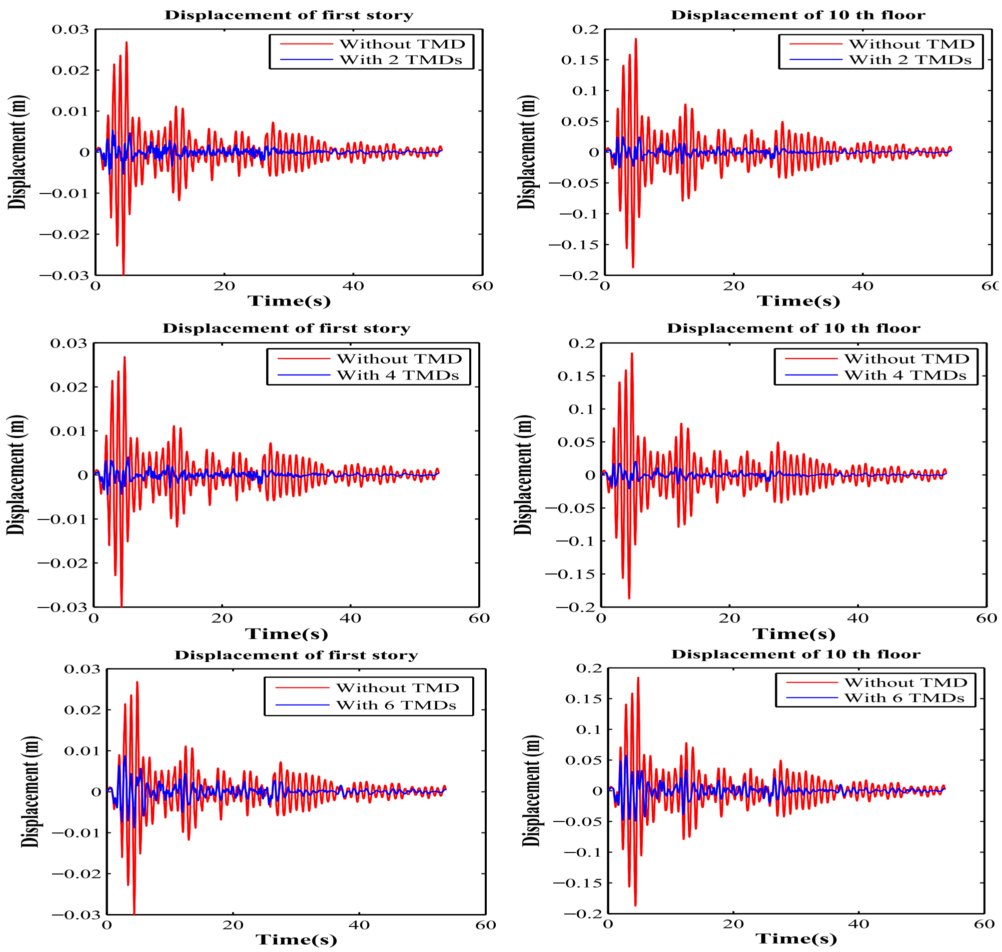

Fig. 7 Maximum first and top stories displacement response of building with and without MTMD under El-Centro 1940 NS

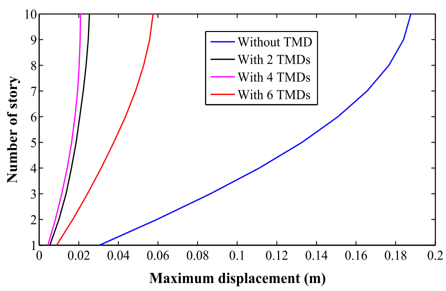

Fig. 8 Maximum displacements of uncontrolled and controlled structure

Table 5 Maximum displacements respect to ground El Centro (1940) NS earthquake

Story	Maximum absolute displacement respect to ground (m)							
	Without TMD	With TMD						
		GA (Hadi nd Arfiadi 1998)	Numerical method (Lee *et al.* 2006)	HS (Bekdaş and Nigdeli 2011)	CSS (Kaveh *et al.* 2015)	Present study (ESSA)		
						2TMDs	4TMDs	6TMDs
1	0.031	0.019	0.020	0.016	0.0185	0.0054	0.0044	0.0088
2	0.060	0.037	0.039	0.031	0.0362	0.0100	0.0082	0.0170
3	0.087	0.058	0.057	0.044	0.0525	0.0136	0.0114	0.0244
4	0.112	0.068	0.073	0.057	0.0682	0.0163	0.0142	0.0313
5	0.133	0.082	0.087	0.068	0.0825	0.0187	0.0164	0.0377
6	0.151	0.094	0.099	0.078	0.0950	0.0205	0.0181	0.0436
7	0.166	0.104	0.108	0.087	0.1056	0.0223	0.0194	0.0487
8	0.177	0.113	0.117	0.094	0.1139	0.0237	0.0202	0.0528
9	0.184	0.119	0.123	0.099	0.1196	0.0248	0.0207	0.0558
10	0.188	0.122	0.126	0.102	0.1225	0.0254	0.0209	0.0575

Table 6 Properties of 10 story building (*Ex. 2*)

Story	Mass (ton)	Stiffness (M N/m)
1	179	62.470
2	170	52.260
3	161	56.140
4	152	53.020
5	143	49.910
6	134	46.790
7	125	43.670
8	116	40.550
9	107	37.430
10	98	34.310

Table 7 Upper and lower bounds for each TMD parameters (Ex. 2)

	m_d	c_d	k_d
Number of TMDs	n=2,4,6	n=2,4,6	n=2,4,6
Lower bound	2	0.01	0.1
Upper bound	18	0.4	2.5

Table 8 Optimum MTMD parameters obtained from ESSA (*Ex. 2*)

	Case 1 (n=2)		Case 2 (n=4)				Case 3 (n=6)					
$m_d(t)$	14.9	7	17.58	6.67	11.02	2.65	2	7.09	8.37	7.50	4.6	8.65
$c_d\left(MN\frac{s}{m}\right)$	0.162	0.03	0.39	0.3	0.39	0.38	0.22	0.19	0.24	0.24	0.07	0.206
$k_d\left(\frac{MN}{m}\right)$	0.165	1.52	0.185	2.36	0.71	0.47	0.12	1.37	1.18	0.1	0.77	2.14

maximum number of iteration, population size and number of TMD, and also by adjusting the upper and lower bound for the TMD parameters to be used in ESSA (shown in Table 7), optimum MTMD parameters for all three cases under El-Centro 1940 NS ground acceleration record, are obtained as Table 8.

By setting optimum parameters of MTMD in each case, maximum first and top story displacement response of building and also the maximum displacements of each floor with and without MTMD in three cases are shown in Fig. 9 and Fig. 10, respectively.

To compare the results of this model with other researcher's results, Table 9 is collected. It can be deduced from Table 9 that, the ESSA has an acceptable performance in dealing with the optimization of the MTMD parameters, and can better control the structural response in comparison with other optimization algorithms. For example, the maximum top story displacement using classical design method by Den Hartog (1985), Warburton (1982) and Sadek *et al.* (1997) are reduced from 0.327m to 0.276 (15.5%), 0.310 (5.2%) and 0.281 (14.0%), respectively. Also, using GA (Hadi and Arfiadi 1998), HS (Bekdaş and Nigdeli 2011) and CSS (Kaveh *et al.* 2015), the maximum top story displacement is reduced from 0.327m to 0.272 (16.8%), 0.205 (37.3%) and 0.242 (25.9%), respectively. However, using ESSA, the maximum top story displacement is

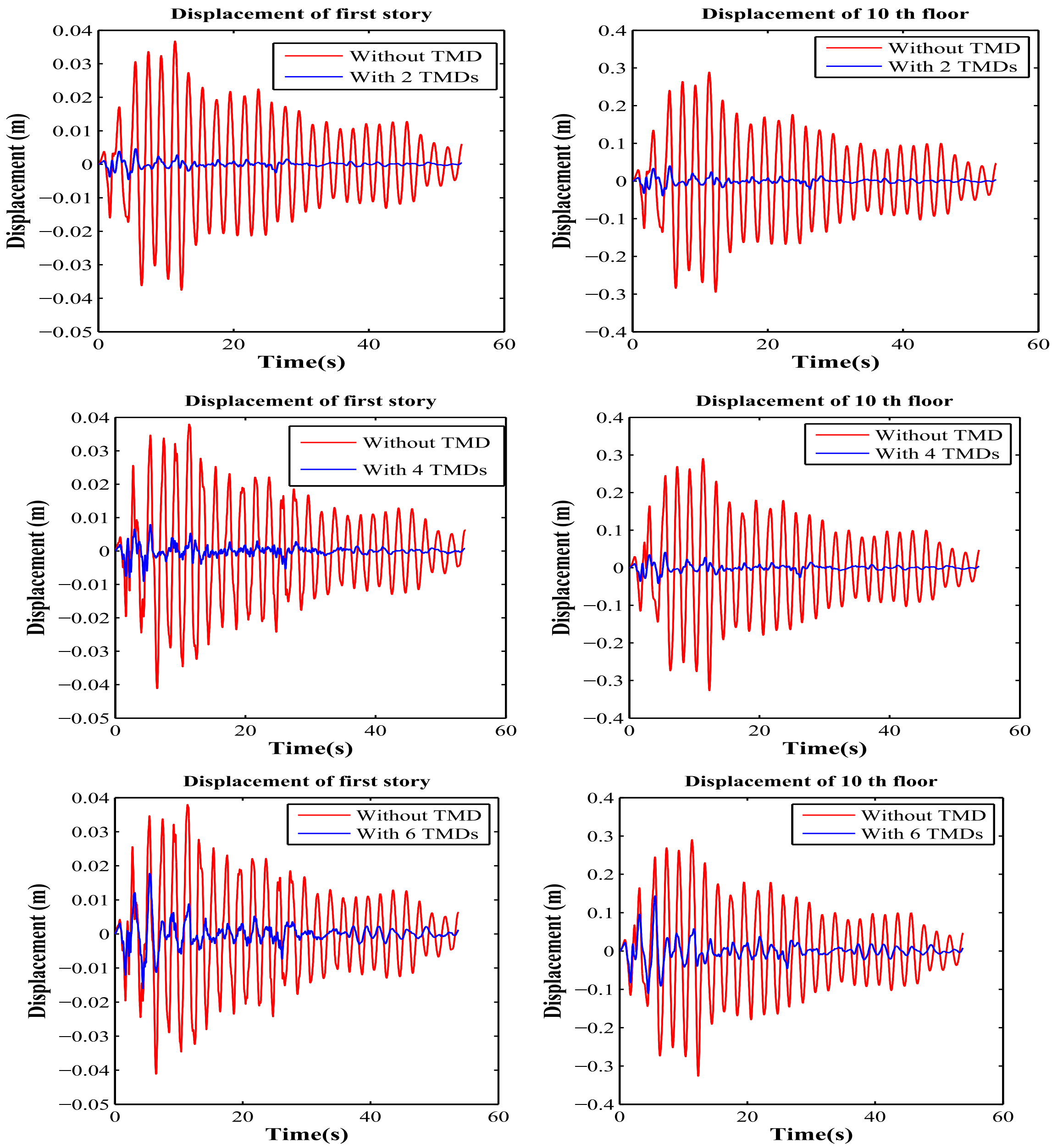

Fig. 9 Maximum first and top story displacement response of building with and without MTMD under El-Centro 1940 NS record (Ex. 2)

Table 9 Maximum displacements respect to ground El Centro (1940) NS earthquake (*Ex. 2*)

Story	Without TMD	Den Hartog (1985)	Warburton (1982)	Sadek *et al.* (1997)	GA (Hadi and Arfiadi 1998)	HS (Bekdaş and Nigdeli 2011)		Present study (ESSA) 2TMDs	Present study (ESSA) 4TMDs	Present study (ESSA) 6TMDs
1	0.041	0.034	0.036	0.036	0.034	0.027	0.030	0.010	0.009	0.017
2	0.088	0.074	0.079	0.077	0.072	0.058	0.655	0.022	0.016	0.038
3	0.129	0.106	0.114	0.113	0.0525	0.083	0.094	0.033	0.023	0.057
4	0.166	0.136	0.147	0.145	0.134	0.105	0.120	0.043	0.027	0.075
5	0.197	0.163	0.177	0.172	0.160	0.124	0.143	0.053	0.031	0.092
6	0.222	0.187	0.206	0.194	0.184	0.140	0.163	0.062	0.034	0.106
7	0.252	0.213	0.236	0.219	0.210	0.157	0.186	0.070	0.037	0.119
8	0.286	0.239	0.267	0.245	0.236	0.177	0.209	0.077	0.039	0.130
9	0.313	0.261	0.292	0.266	0.258	0.195	0.229	0.083	0.040	0.138
10	0.327	0.276	0.310	0.281	0.272	0.205	0.242	0.087	0.041	0.143

Maximum absolute displacement respect to ground (m) reduced to 0.087 (73.3%), 0.041 (87.4%) and 0.143 (56.2%) in the cases of using two, four and six TMDs.

5. Conclusions

This paper investigates the efficiency of the new proposed enhanced salp swarm algorithm (ESSA) in dealing with optimization problems. SSA like other optimization algorithms has some defects such as low convergence rate and sticking in the local optima. To overcome these problems, OBL and MF methods are added to SSA which enhanced its exploration and exploitation capabilities. To examine its performance, two kinds of problems, mathematical and engineering problems, are selected. Considering mathematical benchmark test functions, it is proved that ESSA has better performance than standard SSA in finding optimum values. Also, the convergence rate of the ESSA has become better than SSA. For the engineering problems, two benchmark buildings equipped with MTMD are chosen to find the optimum parameters of the control device. Reducing the structural response subjected to earthquake excitation considering the optimum parameters for the MTMD is the criterion for evaluating the performance of the proposed algorithm in these examples.

In the first example, the maximum first story displacement of the building using GA (Hadi and Arfiadi (1998), numerical method (Lee *et al*. 2006), HS (Bekdaş and Nigdeli 2011) and CSS (Kaveh *et al*. 2015), are reduced from 0.031m to 0.019 (38.7%), 0.020 (35.5%), 0.016 (48.38%) and 0.0185 (40.32%), respectively. However, the new ESSA can achieve a reduction to 0.0054 (82.5%), 0.0044 (85.8%) and 0.0088 (71.6%) in the cases of using two, four and six TMDs.

As the second engineering problem, a ten-story benchmark building equipped with TMD is considered and results of the investigation show that the maximum top story displacement using classical design method by Den Hartog (1985), Warburton (1982) and Sadek *et al*. (1997) are reduced from 0.327m to 0.276 (15.5%), 0.310 (5.2%) and 0.281 (14.0%), respectively. Also, using GA (Hadi and Arfiadi 1998), HS (Bekdaş and Nigdeli 2011) and CSS (Kaveh *et al*. 2015), the maximum top story displacement is reduced from 0.327m to 0.272 (16.8%), 0.205 (37.3%) and 0.242 (25.9%), respectively. However, using ESSA, the maximum top story displacement is reduced to 0.087 (73.3%), 0.041 (87.4%) and 0.143 (56.2%) in the cases of using two, four and six TMDs, which shows the superiority of the ESSA over other mentioned algorithms in facing with optimum design of the TMDs

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