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Full Length Research Paper

Design optimisation of dome structures by enhanced genetic algorithm with multiple populations

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The design of dome structures is optimized by a genetic algorithm methodology with multi populations. In order to increase the convergence degrees of optimal designs obtained, exploitation and exploration capacities of the genetic algorithm methodology are enhanced. In this regard, a radial basis neural network and a new design strategy based on provisions of LRFD_AISC V3 specification are implemented into the optimization procedure. Furthermore, the size-shape-topology design variables are simultaneously utilized to automatically generate both sphere and ellipse-shaped dome structures. The computational performance of the proposed optimization approach named as enhanced genetic algorithm with multiple populations (EGAwMP) is evaluated considering the design optimization of two dome structures. It is demonstrated that the proposed optimization approach succeed in obtaining optimal designs with higher converged degree. Furthermore, it is displayed that using the size-shape-topology design variables for a sphere-shaped dome structure increases the optimality quality of designs compared to those obtained by using size-shaped-design variables for an ellipse-shaped dome structure. Consequently, the proposed optimization approach is recommended to optimize the design of dome structures as an intelligence optimization tool.

Key words: Genetic algorithm, multiple populations, neural network, domes, LRFD-AISC.

INTRODUCTION

The dome structures, which of member properties are assigned from a ready steel profile list are preferably used to cover large span areas due to its higher carrying capacity and aesthetic feature (Saka and Kameshki, 1998; Kameshki and Saka, 2007; Saka, 2007; Hasancebi et al., 2009a). Particularly, possibility of constructing it in considerably lower costs increases its popularity. In other hand, the variety in steel profiles with tube-shaped cross-sections is a big impact on a designer who has a responsibility of determining the lightest dome design. Therefore, the best way is to utilize an optimization tool for the design of dome structures to reduce its constructing cost. Although, initially mathematical programming techniques governed by the design variables of continuous type have been used as an optimization tool, the design variables generated have not been correctly matched to available cross-sectional properties in a ready steel profile list. Furthermore, when a solution space has irregular peaks, these gradient based approaches do not achieve to obtain fair and accurate gradient information. Therefore, stochastic search methods governed by probabilistic transition rules have been developed as an alternative to these deterministic approaches (Saka, 2007). Especially, meta-heuristic search algorithms based on simulation of natural phenomena become more successful in drawing more attention of designers due to their capability of both hybridizing with each other and extending by various modifications. The simplest and primary one of these algorithms is Simple Genetic Algorithm (SGA) (Goldberg, 1989). SGA based on Darwinian's natural selection theorem is widely utilized as an optimization tool in various structural engineering field (Saka, 1998; Ali and Saka, 1999; Saka et al., 2000; Kameshki and Saka, 2001).

SGA uses a population of potential designs for exploration of an optimal design. The population, each of which is represented by a coded chromosome is maintained by genetic operators like mutation, crossover and selection etc. This genetic search is terminated after a pre-defined generation number is completed. Although, SGA has a simple genetic search mechanism, both higher interaction between genetic operators (large number of genetic operator parameters) and complexity in design problem (large number of design variables, design constraints and large size of search space, etc) causes a stagnation in the genetic search (Talaslioglu, 2009). Furthermore, using operator parameters with fixed values prevents to accurately adopt the genetic search to a varying genetic environment; hence, the computational cost of optimization procedures is correspondingly increased. In order to overcome these shortcomings mentioned, one of the remedies is to divide an entire population into sub-populations. However, it was demonstrated that SGA with multiple populations for design optimization of steel structures slightly affects the convergence degree of optimal designs due to usage of genetic parameters with pre-determined values (Talaslioglu, 2009). In this study, SGA with multiple populations is enhanced by an implementation of both a radial-basis neural network to adaptively adjust parameter values of genetic operators and a new design strategy based on provisions of LRFD_AISC V3 (Load and Resistance Factor Design_American Institute of Steel Construction, Version 3) specification. The adjusted genetic parameter values are correspondingly distributed to related sub-populations obtained by division of an entire population into small ones. Furthermore, the neural network implementation is also used to predict the design variables considering a 'feasible solution pool', which is updated at each generation. Then, predicted design variables are utilized to re-create the population for the next generation depending on an activation of this design strategy.

The 'worst feasible solution' in the feasible solution pool indicates the maximum weight of steel structure that corresponds to a steel construction with the largest tube-shaped cross-sections. Feasible solution with higher quality is the minimum of feasible solution pool obtained at current generation. The 'worst unfeasible solution' indicates the minimum weight of steel structure that corresponds to a steel construction with the smallest tube-shaped cross-sections. A potential feasible solution called 'possible feasible future' is obtained by an implementation of neural networks. In the end of a whole genetic search, optimum design, which contains the design variables corresponding to the minimum value of feasible solution pool is obtained.

OPTIMUM DESIGN OF DOME STRUCTURES

In this study, total weight of a dome structure W is minimized considering design constraints based on provisions of LRFD_AISC V3 specification (Equation 1). The violation of constraints is penalized by a penalty value P. The weight minimization process is formulated as:

$$\min\ W = \sum_{k=1}^{m} (w * l)_k + P \quad (k = 1,...,m) \tag{1}$$

Where,

$$P = (r_0 * t)^{\varphi} * \left(\sum_{k=1}^{m} g_{slend}^{k} + \sum_{k=1}^{m} g_{axial}^{k} + \sum_{k=1}^{m} g_{mom}^{k} + \sum_{k=1}^{m} g_{shear}^{k} + \sum_{j=1}^{n} g_{disp}^{j}\right) * f \tag{2}$$

The constants used in the penalization formulation are taken as $r_0 = 0.50$, $\varphi = 2$, $f = 10$ and t = current generation number as given in Hasancebi and Erbatur (1999) (Equation 2). In Equation 2, the slenderness, axial strength and flexural strength-related constraints (g_{slend}, g_{axial}, g_{mom}, g_{shear}) are expressed as:

$$\left.\begin{aligned} g_{slend} &= \begin{cases} \dfrac{k_{effect} * L_k}{r} - 300 & :\left(\dfrac{k_{effect} * L_k}{r}\right) > 300 \\ 0 & :\left(\dfrac{k_{effect} * L_k}{r}\right) < 300 \end{cases} \quad (k = 1,...,m) \\ g_{axial} &= \begin{cases} \dfrac{P_{uk}}{(\phi_{c-t} * P_{nk})} - 1 & :(\phi_{c-t} * P_{nk}) < P_{uk} \\ 0 & :(\phi_{c-t} * P_{nk}) > P_{uk} \end{cases} \quad (k = 1,...,m) \end{aligned}\right\} \tag{3}$$

and displacement constraint as:

$$\left.\begin{aligned} g_{mom} &= \begin{cases} \dfrac{M_{uk}}{(\phi_b * M_{nk})} - 1 & :(\phi_b * M_{nk}) < M_{uk} \\ 0 & :(\phi_b * M_{nk}) > M_{uk} \end{cases} \quad (k = 1,...,m) \\ g_{shear} &= \begin{cases} \dfrac{V_{uk}}{(\phi_s * V_{nk})} - 1 & :(\phi_s * V_{nk}) < V_{uk} \\ 0 & :(\phi_s * V_{nk}) > V_{uk} \end{cases} \quad (k = 1,...,m) \\ g_{disp} &= \begin{cases} \dfrac{d_{ij}}{d_{max}} & :d_{max} < d_{ij} \\ 0 & :d_{max} > d_{ij} \end{cases} \quad (i = 1,...,12 \text{ and } j = 1,...n) \end{aligned}\right\} \tag{4}$$

Where the term W is computed using length of a member l and unit weight w to be selected from w-sections list. While d is termed as a joint displacement corresponding to related degree of freedom denoted by i, the terms n and m indicate total numbers of joint and member. The slenderness-related constraint limited by an upper bound taken as 300 is governed by the parameters, effective length factor k_{effect}, member length L and gyration radius r. Axial force of members P_{uk}, bending moment strength of members M_{uk}, and shear strength of members V_{uk} are limited by allowable nominal axial force P_{nk}, nominal moment strength M_{nk} and nominal shear strength V_{nk}.

Displacements of joints are constrained by an upper limit d_{max}.

In Equations 3 and 4, $\phi_t = 0.90$, $\phi_c = 0.85$, $\phi_b = 0.90$ and $\phi_s = 0.90$ are resistance factors for axial tension-compression, moment and shear. Both the structural analysis of steels structure and provisions of LRFD_AISC V3 specification are formulated in Appendix. It is noted that some application examples which are solved by use of AISC-LRFD V3 provisions are presented in (Segui, 2007).

IMPLEMENTATION DETAILS OF EGAwMP FOR DESIGN OPTIMIZATION OF DOME STRUCTURE

Usage of design variables for generation of proposed sphere and ellipse-shaped dome structures

In this study, optimal designs are obtained by use of both fixed and varying shape of the dome structures. Therefore, total three design variables named size, shape and topology are used for the design optimization. Whereas, size design variable represents the location number of cross-sectional properties in the tube-shaped profile list, shape design variables have certain parameters, radius (R) for a sphere, A, B and C for an ellipse. Topology design variables are represented by horizontal and vertical division numbers. The division numbers determine the horizontal and vertical lines used for constructing a sphere or ellipse-shaped dome. These design variables are coded into the chromosomes, which are used to represent the individuals of an entire population. Therefore, when the horizontal and vertical division numbers change, the number of joint nodes and truss members are correspondingly varied. Furthermore, if the number of member linkage or design variables changes depending on the activation of the design strategy in the following sub-section, then the length of chromosomes correspondingly changes. However, it is known that the length of a chromosome must be fixed for a proper execution of the optimum procedures. Therefore, it fails when the length of chromosome varies throughout the genetic search.

In this study, in order to overcome this task, the length of chromosome is fixed for the current generation, but altered for the next generation.

Search mechanism of EGAwMP based on multi-started genetic search

EGAwMP works with one population *P*, which contains a number of sub-populations (${}_{SPN}SubP_{SPS}$, SPN: number of subpopulations, SPS: size of corresponding subpopulations) (pseudo code in Figure 1). It has a flexibility of assigning different parameter values Par_{All} to the corresponding sub-population at the same time (name of genetic operators in Table 1). The computation of optimization procedure is performed in two nested loop bounded by an outer and inner generation numbers (Par_{OGN}, Par_{IGN}). The first computational loop starts by $Par_{OGN}, Par_{IGN}, Par_{SPN}, Par_{Mig}^{MI}$ and Par_{Comp}^{CI}. After all individuals of first population are filled by the worst feasible solution (corresponding to maximum weight) against the risk of un-exploration of any feasible solution in the first generation, the parameter values of genetic operators are generated randomly for the first generation. Fitness values *F* are computed following computation of decoded values of *P*. Then, a number of genetic operators (selection, mutation, crossover etc.) are sequentially executed for *P*. The run of genetic search is terminated when the loop reaches to a specified value of Par_{OGN}. The inner loop, which is limited by a specified value of Par_{IGN} has a responsibility of applying a number of genetic operators to the current population.

The computational procedures of migration, competition and selection operators are borrowed from a ready optimization tool called GEATbx (Polheim, 1998) coded in MATLAB (The MathWorks, Inc., Natick, MA, 2008) and adopted for EGAwMP. Then, Evolution History Function (EHF) is computed taking into account of a column matrix called F^{Feas} (Figure 1). According to the value of EHF, both parameter values of genetic operators Par_{ALL} and design variable values $DV_{Possible\_Feasible\_Future}$ (DV_{PFF}) are re-generated by implementation of a neural network (Figure 2). In this regard, a radial basis network with two layers, which is utilized for approximation of any mathematical function is chosen as a neural network model. The radial basis network has no neurons at initial stage and adds neurons to its hidden layer until a specified mean squared error goal is met (default is 0.00). Furthermore, it is governed by a parameter named ‘spread’. It is noted that the use of a higher spread value causes an increase in the number of neurons for training the network. Therefore, spread is taken as 0.4. After an implementation of Neural Network for predication of design variables, DV_{PFF} is used to re-create a new population $[P]$ using the current population$[P]$. The re-creation process is performed in a function named “Design Strategy” (Figure 1). In fact, this function is employed to execute computational procedures of the proposed design strategy based on provisions of LRFD_AISC V3 specification. The re-creation of new population $[P]$ according to the feasible solution pool is formulated by Equation 5 and sketched in Figure 3. In fact, the re-creation approach which was firstly utilized in the development of a genetic algorithm methodology (Talaslioglu, 2009) is re-adopted for EGAwMP by Equation 5.

Computational procedures of the proposed design strategy are managed by un-penalization degree of a

$\text{Par}_{\text{OGN}} = 10, \text{Par}_{\text{IGN}} = 100, \text{Par}_{\text{SPN}} = 5, \text{MinFeasPrev} = 1\text{xE}9$, Apply_Des_Str=1,

for i = 1 : Par_{OGN}

if i==1

%use randomized values

$$\begin{aligned}\text{Par}_{\text{All}} = [[\,_{1}\text{Par}_{\text{SPS}} \quad _{2}\text{Par}_{\text{SPS}} \quad . \; . \quad _{\text{SPN}}\text{Par}_{\text{SPS}}] \quad [\,_{1}\text{Par}^{\text{IR}}_{\text{Sel}} \quad _{2}\text{Par}^{\text{IR}}_{\text{Sel}} \quad . \; . \quad _{\text{SPN}}\text{Par}^{\text{IR}}_{\text{Sel}}] \\ [\,_{1}\text{Par}^{\text{P}}_{\text{Sel}} \quad _{2}\text{Par}^{\text{P}}_{\text{Sel}} \quad . \; . \quad _{\text{SPN}}\text{Par}^{\text{P}}_{\text{Sel}}] \quad [\,_{1}\text{Par}^{\text{GG}}_{\text{Sel}} \quad _{2}\text{Par}^{\text{GG}}_{\text{Sel}} \quad . \; . \quad _{\text{SPN}}\text{Par}^{\text{GG}}_{\text{Sel}}] \quad [\,_{1}\text{Par}^{\text{CR}}_{\text{Cros}} \quad _{2}\text{Par}^{\text{CR}}_{\text{Cros}} \quad . \; . \quad _{\text{SPN}}\text{Par}^{\text{CR}}_{\text{Cros}}] \\ [\,_{1}\text{Par}^{\text{MR}}_{\text{Mut}} \quad _{2}\text{Par}^{\text{MR}}_{\text{Mut}} \quad . \; . \quad _{\text{SPN}}\text{Par}^{\text{MR}}_{\text{Mut}}] \quad [\,_{1}\text{Par}^{\text{MI}}_{\text{Mig}} \quad _{2}\text{Par}^{\text{MI}}_{\text{Mig}} \quad . \; . \quad _{\text{SPN}}\text{Par}^{\text{MI}}_{\text{Mig}}] \quad [\,_{1}\text{Par}^{\text{MR}}_{\text{Mig}} \quad _{2}\text{Par}^{\text{MR}}_{\text{Mig}} \quad . \; . \quad _{\text{SPN}}\text{Par}^{\text{MR}}_{\text{Mig}}] \\ [\,_{1}\text{Par}^{\text{MT}}_{\text{Mig}} \quad _{2}\text{Par}^{\text{MT}}_{\text{Mig}} \quad . \; . \quad _{\text{SPN}}\text{Par}^{\text{MT}}_{\text{Mig}}] \quad [\,_{1}\text{Par}^{\text{CI}}_{\text{Comp}} \quad _{2}\text{Par}^{\text{CI}}_{\text{Comp}} \quad . \; . \quad _{\text{SPN}}\text{Par}^{\text{CI}}_{\text{Comp}}] \quad [\,_{1}\text{Par}^{\text{CR}}_{\text{Comp}} \quad _{2}\text{Par}^{\text{CR}}_{\text{Comp}} \quad . \; . \quad _{\text{SPN}}\text{Par}^{\text{CR}}_{\text{Comp}}] \\ [\,_{1}\text{Par}^{\text{NSC}}_{\text{Comp}} \quad _{2}\text{Par}^{\text{NSC}}_{\text{Comp}} \quad . \; . \quad _{\text{SPN}}\text{Par}^{\text{NSC}}_{\text{Comp}}]]\end{aligned}$$

$[\text{Par}_{\text{All}}] = \text{Rand}([\text{Par}_{\text{All}}])$

%initialize $[\text{P}] = [\,_{1}\text{SubP}_{\text{SPS}} \quad _{2}\text{SubP}_{\text{SPS}} \quad . \; . \quad _{\text{SPN}}\text{SubP}_{\text{SPS}}]$, using randomized values limited within $[\text{Par}_{\text{UDV}}, \text{Par}_{\text{LDV}}]$

Initialize($[\text{P}], \text{Par}_{\text{UDV}}, \text{Par}_{\text{LDV}}$)

%a string of binary – coded design variables which represents possible maximum weight corresponding to

%the worst feasible solution

$[\text{P}^{\text{Feas}}] = [1001101...]$

$[\text{P}^{\text{d}}_{\text{Feas}}] = \text{Decoding}([\text{P}^{\text{Feas}}])$

$[\text{F}^{\text{Feas}}] = \text{Fitness\_Calculation}(\text{Problem\_name}, \text{Par}_{\text{ND}}, [\text{P}^{\text{d}}_{\text{Feas}}])$

$[[\text{P}^{\text{Feas}}],[\text{F}^{\text{Feas}}]] = \text{Collect\_Feasible\_Solutions}(\text{P}^{\text{Feas}}, \text{F}^{\text{Feas}})$

end

for j= 1 : Par_{IGN}

$[\text{P}^{\text{d}}] = \text{Decoding}([\text{P}])$

$[\text{F}] = \text{Fitness\_Calculation}(\text{Problem\_name}, \text{Par}_{\text{ND}}, [\text{P}^{\text{d}}])$

$[[\text{P}^{\text{Feas}}],[\text{F}^{\text{Feas}}]] = \text{Collect\_Feasible\_Solutions}([\text{P}^{\text{Feas}}],[\text{F}^{\text{Feas}}],[\text{P}],[\text{F}])$

$[\text{F}] = \text{Ranking}([\text{F}], \text{Par}^{\text{GG}}_{\text{Sel}}, \text{Par}^{\text{P}}_{\text{Sel}})$

$[\text{P}] = \text{Selection}([\text{P}],[\text{F}], \text{Par}^{\text{P}}_{\text{Sel}}, \text{Par}^{\text{GG}}_{\text{Sel}})$

$[\text{P}] = \text{Mutation}([\text{P}], \text{Par}^{\text{MR}}_{\text{Mut}})$

$[\text{P}] = \text{Crossover}([\text{P}], \text{Par}^{\text{CR}}_{\text{Cros}})$

$[\text{P}] = \text{Control}([\text{P}], \text{Par}_{\text{UDV}}, \text{Par}_{\text{LDV}})$ % randomly generate $[\,^{i}_{j}\text{P}]$ if not within the limits of $(\text{Par}_{\text{UDV}}, \text{Par}_{\text{LDV}})$

$[\text{P}^{\text{d}}] = \text{Decoding}([\text{P}])$

$[\text{F}] = \text{Fitness\_Calculation}(\text{Problem\_name}, \text{Par}_{\text{ND}}, [\text{P}^{\text{d}}])$

$[[\text{P}^{\text{Feas}}],[\text{F}^{\text{Feas}}]] = \text{Collect\_Feasible\_Solutions}([\text{P}^{\text{Feas}}],[\text{F}^{\text{Feas}}],[\text{P}],[\text{F}])$

$[\text{F}] = \text{Ranking}([\text{F}], \text{Par}^{\text{GG}}_{\text{Sel}}, \text{Par}^{\text{P}}_{\text{Sel}})$

$[\text{P}] = \text{Competation}([\text{P}],[\text{F}], \text{Par}^{\text{CI}}_{\text{Comp}}, \text{Par}^{\text{CR}}_{\text{Comp}}, \text{Par}^{\text{NSC}}_{\text{Comp}})$

$[\text{P}] = \text{Migration}([\text{P}],[\text{F}], \text{Par}^{\text{MI}}_{\text{Mig}}, \text{Par}^{\text{MR}}_{\text{Mig}}, \text{Par}^{\text{MT}}_{\text{Mig}})$

end % for j= 1 : Par_{IGN}

$$\text{EHF} = \text{Best}([\text{F}^{\text{Feas}}]) - \frac{\text{Best}([\text{F}^{\text{Feas}}]) - \text{Possible Minimum Weight Corresponding to Worst Unfeasible Solution}}{\text{Par}_{\text{OGN}}}$$

$[\text{Par}_{\text{All}}] = \text{Neural Network Implementation}(\text{Par}_{\text{All}}, \text{EHF})$

$\text{DV}_{\text{Possible\_Feasible\_Future}} = \text{Neural Network Implementation}([\text{P}^{\text{Feas}}],[\text{F}^{\text{Feas}}], \text{EHF})$

if ($i \geq 2$) & (Apply_Des_Str == 1)

$[\text{P}, \text{Par}_{\text{ND}}] = \text{Design\_Strategy}([\text{P}], \text{DV}_{\text{Possible\_Feasible\_Future}}, \text{Par}_{\text{ND}}, \text{Par}_{\text{UDV}} \text{ and } \text{Par}_{\text{LDV}})$

end

end % for i = 1 : Par_{OGN}

Figure 1. A Pseudo code for EGAwMP.

Table 1. Genetic operators and their related parameters (Figure 1 for Par_{All}).

Operator name	Parameter name and its abbreviation	Method	Static parameter value	Dynamic parameter value
-	Minimum of feasible solutions obtained previously MinFeasPrev	-	1xE9	
-	Application of design strategy Apply_Des_Str		1(yes) or 0(No)	
-	Number of outer generation Par_{OGN}	-	10	-
-	Number of inner generation Par_{IGN}	-	100	-
-	Number of sub-population Par_{SPN}	-	5	-
-	Sub-population size Par_{SPS}	-	-	1< <20* and 1< <30*
-	Number of design variables, their upper and lower bounds Par_{ND}, Par_{UDV}, Par_{LDV}	-	Depends on design problem	-
	Insertion rate Par_{Sel}^{IR}	-	-	(0< <1)*
	Insertion method	Fitness based selection	-	-
Selection (stochastic universal sampling)	Pressure Par_{Sel}^{P}	-	-	(1< <2)*
	Ranking method	Non-linear Ranking	-	-
	Generation gap Par_{Sel}^{GG}	-	-	(1< <2)*
Crossover (single point crossover)	Crossover rate Par_{Cros}^{CR}	-	-	(0< <1)*
Mutation (single point mutation)	Mutation rate Par_{Mut}^{MR}	-	-	(0< <1)*
	Migration interval Par_{Mig}^{MI}	-	1	-
Migration	Migration rate Par_{Mig}^{MR}	-	-	(0< <1)*
	Migration topology Par_{Mig}^{MT}	Neighborhood (1) and Ring (2)	-	1 or 2
	Migration selection	Best individual	-	-
	Competition interval Par_{Comp}^{CI}	-	1	-
Competition	Competition rate Par_{Comp}^{CR}	-	-	(0< <1)*
	Number of sub-population Par_{Comp}^{NSC} for competition	-	-	(1< <SN)*

*Adaptively adjusted for each population.

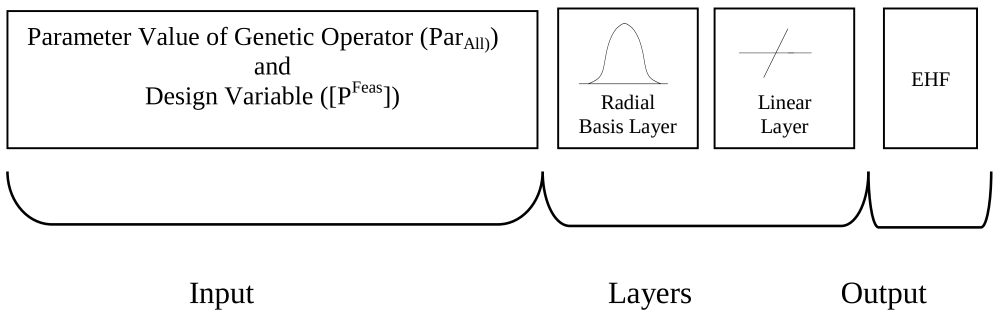

Figure 2. A radial-basis neural network used for predicting genetic operator parameters.

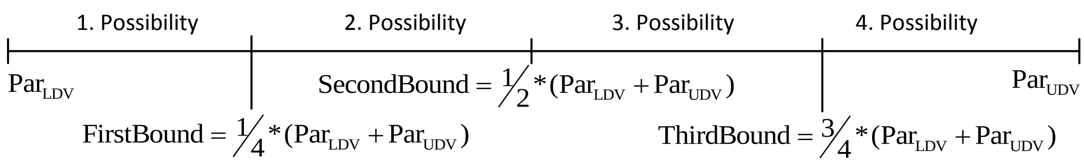

Figure 3. Possibilities used in re-creation of population.

feasible solution defined by a ratio of available strength of steel structure members to their allowable nominal strength called 'unity' (Equations 3 and 4). The allowable nominal strengths of steel structure members are computed according to the provisions of LRFD_AISC V3 specification. In order to increase the exploration capability of EGAwMP, maximum unities of steel structure members, unity_max (Equation 6) are stored in a pool called unity_max_pool. Thus, the most conflicted members of steel structure are determined according to the history of unity_max recorded. If a feasible solution with a higher quality is not obtained in current generation, the conflicted members of steel structure are discarded from the corresponding group and receive a different design variable number. The main advantage of this design strategy is its ability of evaluating the sensitivity degree of each member towards a number of simultaneous loading conditions.

$$\begin{bmatrix} P_1^1 & . & P_1^m \\ . & . & . \\ P_k^1 & . & P_k^m \end{bmatrix} = \begin{cases} \begin{cases} \text{rand}(Par_{LDV} - \text{FirstBound}) \quad , & 1 \le k < TPS * 45/100 \\ \text{rand}(\text{FirstBound} - \text{SecondBound}) \, , & TPS*45/100 \le k < TPS*70/100 \\ \text{rand}(\text{SecondBound} - \text{ThirdBound}), & TPS*70/100 \le k < TPS*85/100 \\ \text{rand}(Par_{UDV} - \text{ThirdBound}) & TPS*85/100 \le k < TPS \end{cases} & \text{, if } Par_{LDV} \le {}^m DV_{PFF} < \text{FirstBound} \quad \text{(1.Possibility)} \\ \begin{cases} \text{rand}(Par_{LDV} - \text{FirstBound}) \quad , & 1 \le k < TPS*25/100 \\ \text{rand}(\text{FirstBound} - \text{SecondBound}) \, , & TPS*25/100 \le k < TPS*70/100 \\ \text{rand}(\text{SecondBound} - \text{ThirdBound}), & TPS*70/100 \le k < TPS*85/100 \\ \text{rand}(Par_{UDV} - \text{ThirdBound}) \, , & TPS*85/100 \le k < TPS \end{cases} & \text{,if FirstBound} \le {}^m DV_{PFF} < \text{SecondBound} \quad \text{(2.Possibility)} \\ \begin{cases} \text{rand}(Par_{LDV} - \text{FirstBound}) & 1 \le k < TPS*15/100 \\ \text{rand}(\text{FirstBound} - \text{SecondBound}) \, , & TPS*15/100 \le k < TPS*30/100 \\ \text{rand}(\text{SecondBound} - \text{ThirdBound}), & TPS*30/100 \le k < TPS*75/100 \\ \text{rand}(Par_{UDV} - \text{ThirdBound}) \, , & TPS*75/100 \le k < TPS \end{cases} & \begin{array}{l} \text{, if SecondBound} \le {}^m DV_{PFF} < \text{ThirdBound} \\ \text{(3.Possibility)} \\ m = 1, \ldots, Par_{NDV} \\ TPS = Par_{SPS} * Par_{SPN} \\ k = 1, \ldots, TPS \end{array} \\ \begin{cases} \text{rand}(Par_{LDV} - \text{FirstBound}) \quad , & 1 \le k < TPS*45/100 \\ \text{rand}(\text{FirstBound} - \text{SecondBound})., & TPS*45/100 \le k < TPS*70/100 \\ \text{rand}(\text{SecondBound} - \text{ThirdBound}), & TPS*70/100 \le k < TPS*85/100 \\ \text{rand}(Par_{UDV} - \text{ThirdBound}) & TPS*85/100 \le k < TPS \end{cases} & \text{,if ThirdBound} \le {}^m DV_{PFF} < Par_{UDV} \quad \text{(4.Possibility)} \end{cases} \quad (5)$$

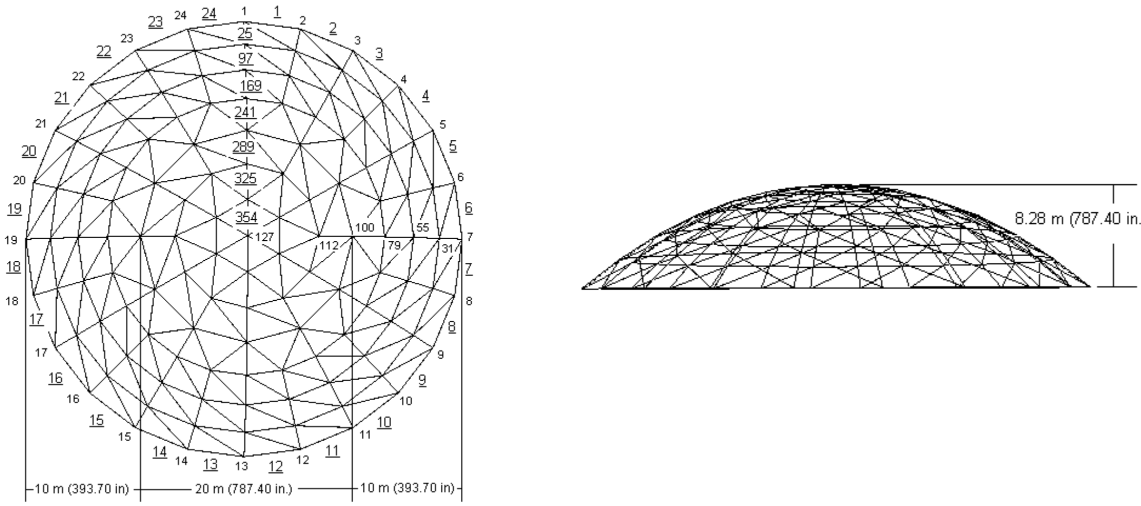

Figure 4. A dome structure with 354-bar.

$$\text{Unity\_max} = \max\left(\frac{P_{uk}}{(\phi_{c-t} * P_{nk})}, \frac{M_{uk}}{(\phi_b * M_{nk})}, \frac{V_{uk}}{(\phi_s * V_{nk})}\right) \quad (6)$$

DESIGN EXAMPLES

The two design examples borrowed from the application examples utilized in literature are used to demonstrate the computational performance of EGAwMP. While a benchmark design example (dome structure with 354) is optimized using only size design variables, the last design example is tackled to optimize the design of sphere and ellipse-shaped dome structure using size-shape-topology design variables. Particularly, the design complexity of first design example arisen from the higher spanning length and member number is higher compared to the last one. Thus, it is possible to demonstrate the effectiveness of EGAwMP's components on maintenance of optimal design quality. The last design example with relatively less design complexity is chosen to evaluate the effect of simultaneously using of size, shape and topology design variables on the optimality quality. The design provisions of these application examples are taken from LRFD_AISC V3 specification. Therefore, the number of constraints (for example stability and tension-compression-flexural strength-related constraints) is higher than those used by the optimization approaches in literature. Hence, the computational performance of EGAwMP is assessed under more severe design conditions. According to the proposed technique aforementioned, total generation number is divided into 10 equal intervals (Par_{OGN} = 10). Thus, both the lengths of chromosomes and parameter values of genetic operators are adaptively adjusted to properly execute the optimization procedures of EGAwMP. Optimization procedures of EGAwMP run 10 times for each design examples.

The number of sub-populations is taken as 5 (Par_{SPN} = 5) for this study. The higher number of genetic operator-related parameters prevents simultaneously visualization of their parameter values. In order to demonstrate the importance of neural network implementation for the optimal design of dome structures, the crossover, mutation, migration and competition rates for each sub-population is presented for the design examples.

Benchmark design example: A dome structure with 354-bar

The weight of this dome structure which has a material elasticity module 199947.961 N/mm^2 (29000 ksi) and yielding point 248.211 N/mm^2 (36 ksi) was first minimized by Hasancebi et al. (2009b). It has three load cases which is used to represent various combinations of dead, snow and wind load and calculated according to provisions of ASCE 7-98 (Hasancebi et al., 2009b). This braced dome with a diameter of 40 m (1574.803 in) and height of 8.28 m (325.984 in) has 127 joints and 354 members (Figure 4). Its members are linked into 22 groups (Par_{ND} = 22); hence, size design variables are represented as:

$A1_{(1\text{-}24)}$, $A2_{(25,27,)}$, $A2_{(25,27,29,31,33,35,37,39,41,43,45,47,49,51,53,55,57,59,61,63,65,67,69,71)}$, $A3_{(26,28,30,32,34,36,38,40,42,44,46,48,50,52,54,56,58,60,62, 64,66,68,70,72)}$, $A4_{(73\text{-}96)}$, $A5_{(97,99,101,103,105,107,109,111,113,115,117,119,121,123,125,127,129,131,133,135,137,139,141,143)}$, $A6_{(98,100,102,104,106,108,110,112,114,116,118,120,122,124,126,128,130,132,134,136,138,140,142,144)}$, $A7_{(1454\text{-}168)}$,

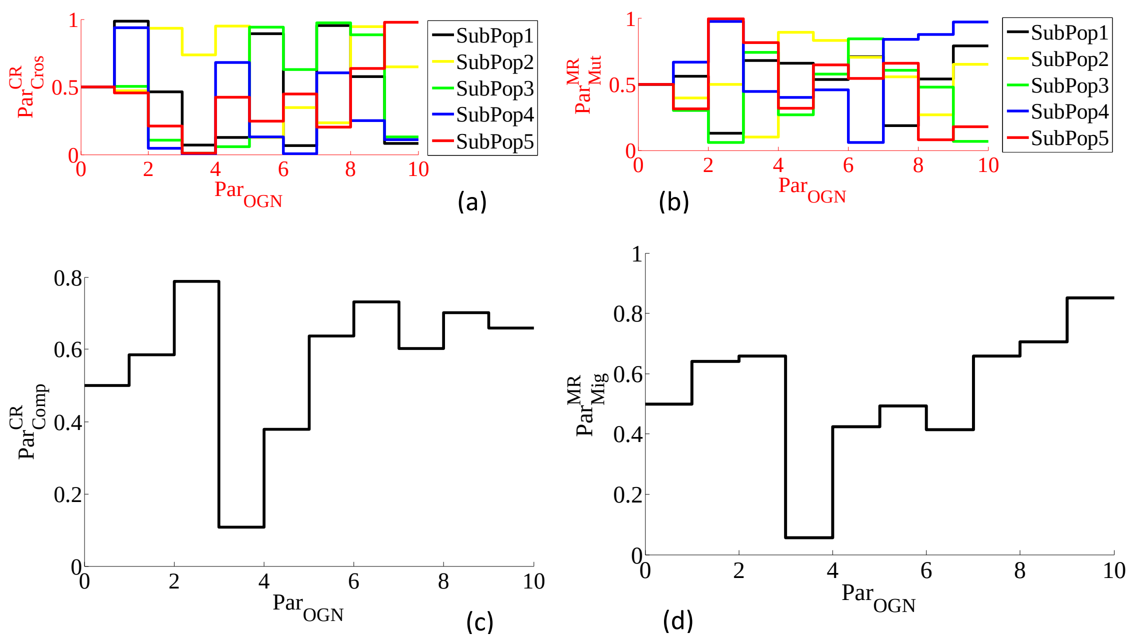

Figure 5. Trend steps for rates of crossover (a), mutation (b), competition (c) and migration (d) (354-bar Dome structure).

A8$_{(169,171,173,175,177,179,181,183,185,187,189,191,193,195,197,199,201,203,205,207,209,211,213,215)}$, A9$_{(170,172,174,176,178,180,182,184,186,188,190,192,194,196,198,200,202,204,206,208,210,212,214,216)}$, A10$_{(217-240)}$, A11$_{(241,244,247,250,253,256,259,262,265,268,271,274)}$, A12$_{(242,245,248,251,254,257,260,263,266,269,272,275)}$, A13$_{(243,246,249,252,255,258,261,264,267,270,273,276)}$, A14$_{(277-288)}$, A15$_{(289,291,293,295,297,299,301,303,305,307,309,311)}$, A16$_{(290,292,294,296,298,300,302,304,306,308,310,312)}$, A17$_{(313-324)}$, A18$_{(325,328,331,334,337,340)}$, A19$_{(326,329,332,335,338,341)}$, A20$_{(327,330,333,336,339,342)}$, A21$_{(343,344,345,346,347,348)}$, A22$_{(349,350,351,352,353,354)}$

It is observed that there is not a certain relationship among the parameters of genetic operators used by crossover (Par_{Cros}^{CR}), mutation (Par_{Mut}^{MR}), migration (Par_{Mig}^{MR}) and competition (Par_{Comp}^{CR}) (Figure 5a to d). Considering convergence history obtained by EGAwMP, it is seen that the proposed design strategy is activated when parameter Par_{OGN} equals to 5 (Figure 6). Due to the fact that the genetic search is stagnated, the members of No 163, 164, 165, 166, 235 and 310 are discarded from corresponding groups and assigned a new group number (unity values of members and displacement values of joints in Figure 7a to d). Thus, the number of groups increases to 22 from 23. The increase in the number of groups leads to an elevation in the number of feasible solution (Table 2). Following the activation of proposed design strategy, EGAwMP achieves to decrease the entire weight of dome structure from 221885.830 N (49881.919 lbf) corresponding to a stagnation situation in genetic search to 141613.912 N (31836.074 lbf) (Table 2).

The optimal weight of dome structure obtained by EGAwMP, 221885.830 N (49881.919 lbf) is also lighter compared to both 275584.677 N (61953.9 lbf) obtained by genetic algorithm with multi-populations ignoring neural network implementation and 144753.999 N (32541.993 lbf) obtained by Hasancebi et al. (2009b) (Table 2). It is obvious that the proposed design strategy leads to acceleration in evolutionary computation of EGAwMP (Figure 6).

A dome with varying size-shape-topology

The entire volume of this dome structure with a radius of 20 m (787.401 in) was firstly minimized by Kaveh and Talatahari (2010) using size design variables. While its material property values are taken as 205 kN/mm^2 (29000 ksi) for elasticity module and 68.95 N/mm^2 (10 ksi) for yielding limit, a vertical downward load of (-500) kN and two horizontal loads of (-100) kN in x and y directions are used to define its loading conditions. In this study, the volume of this dome structure with relatively lower radius (R) compared to first design example is minimized by use of size-shape-topology design variables in order to demonstrate the effectiveness of these design variables on optimality quality of designs. Furthermore, two shape templates, sphere and ellipse are utilized both to obtain practically-applicable-dome shapes from the design optimization and observe the effect of dome shape on the convergence degree of

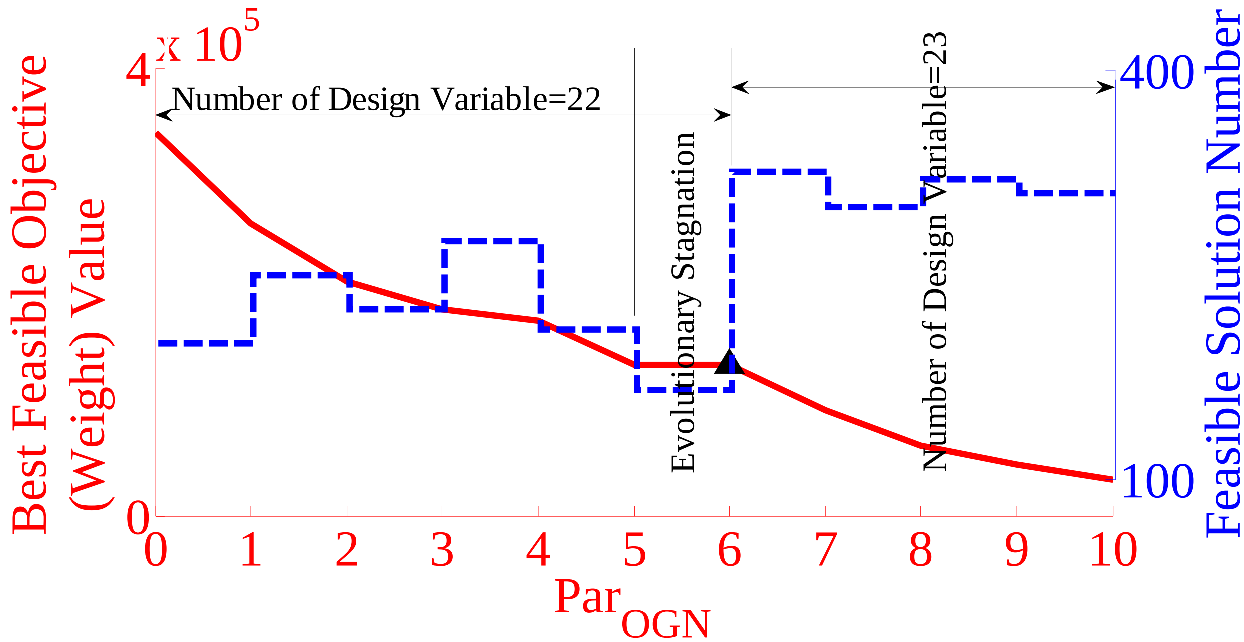

Figure 6. Convergence history of genetic search included optimum design (354-bar Dome structure).

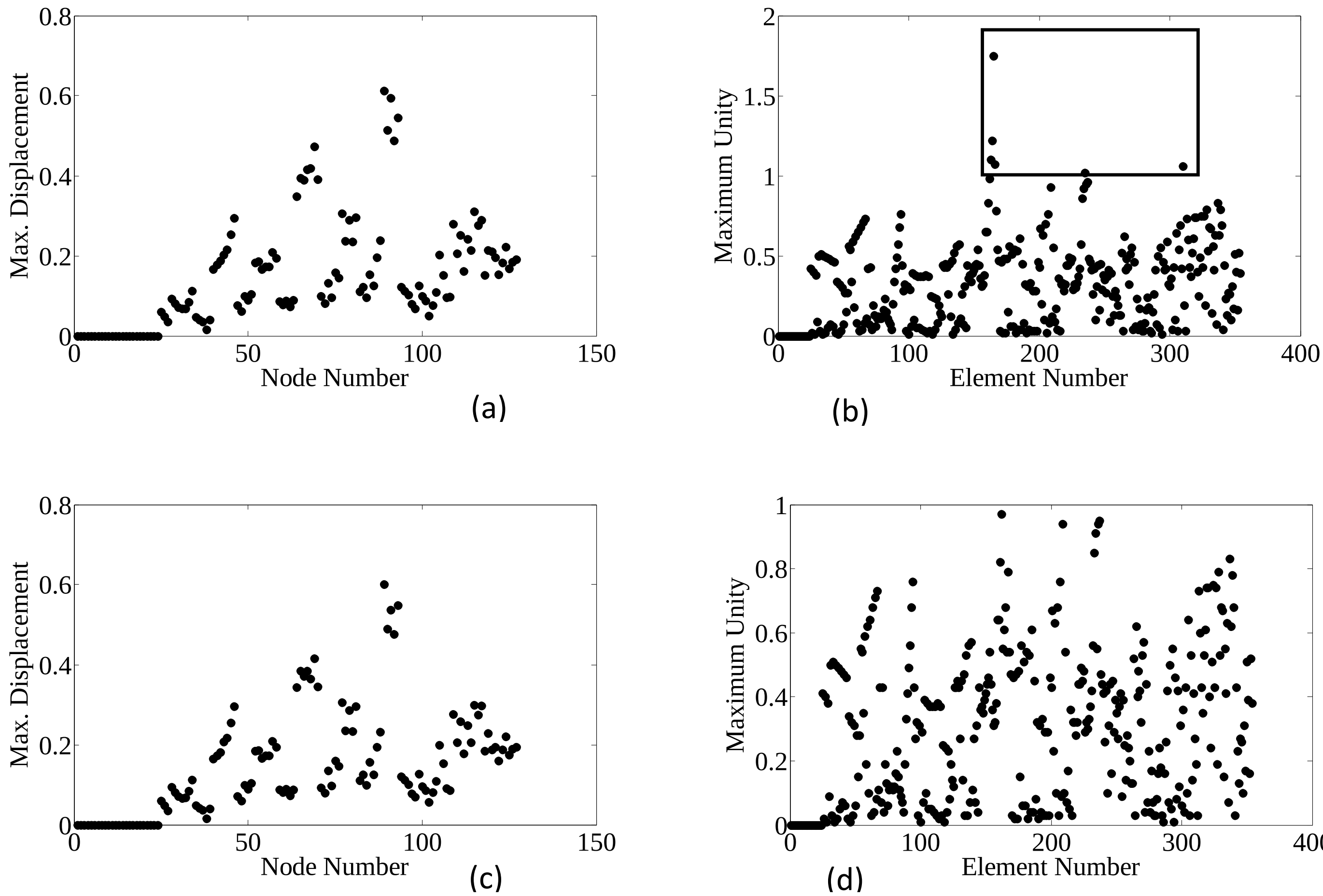

Figure 7. Maximum displacements and Unity_Max vlaues corresponding to feasible solution with higher quality obtained when Par_{OGN} = 5(a-b) and optimum design (c-d) (354-bar dome structure).

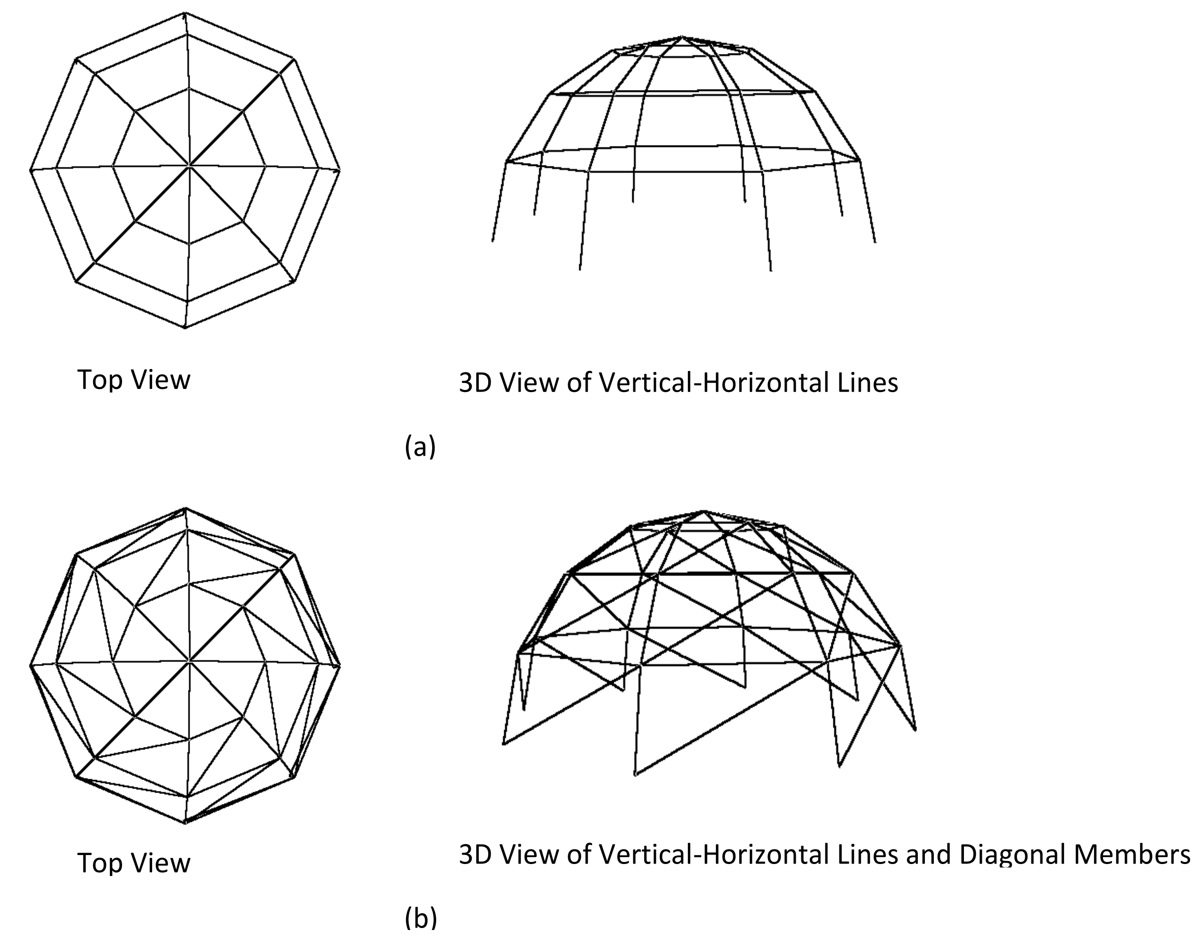

Figure 8. Schematic view of sphere-shaped templates used for Case 1, 3(a) and 2(b).

optimal designs. For this purpose, total of three cases are devised to define a dome topology (Figure 8). Depending on presence of diagonal members, these cases named Case I, II and III are arranged as:

i) It is not used as diagonal member to construct the dome structure. While two size design variables are used to represent the cross-sectional properties of members located on vertical and horizontal lines, two topology design variables are responsible to assign the numbers of horizontal and vertical lines (Figure 8a).

ii) Diagonal members are included into construction of dome structure. While three size design variables are used to represent the cross-sectional properties of members located on vertical, horizontal and diagonal lines, two topology design variables are responsible to assign the numbers of horizontal and vertical lines (Figure 8b).

iii) It is not used as a diagonal member to construct the dome structure. While total number of size design variables is 1+ the number of vertical lines, two topology design variables are responsible to assign the numbers of horizontal and vertical lines (Figure 8a).

Firstly, the parameters of shape design variables of Case I, II and III are adjusted by use of a fixed value, R = 20 m (787.101 in), then varying values in the ranges as 770 and 400 in < R < 800 in. Also, design of ellipse-shaped dome structures is optimized using two parameter value sets of shape design variables: 770 in < A < 800 in, 800 in < B < 850 in and 770 in < C < 800 in and 770 in < A < 800 in, 800 in < B < 850 in and 400 in < C < 800 in. The optimal designs and their fitness values-related statistical data are tabulated according to two topology design variables, horizontal and vertical division numbers (Tables 3, 5 and 7). The parameter values of size and shape design variables corresponding to the optimal designs of sphere and ellipse-shaped dome structures are presented in Tables 4, 6 and 8. It is mentioned that the flexibility of EGAwMP is increased using sphere and ellipse-shaped templates to form geometrical configurations of dome structure with varying shapes. In this regard, the execution of EGAwMP for design optimization of sphere and ellipse shaped dome structure with fixed and varying radius is resulted with corresponding convergence histories of genetic searches (Figures 9 and 12). It is clear that the proposed design

Table 2. Comparison of optimum designs (354-bar spatial truss structure).

Size design variable number	The worst unfeasible solution	Feasible solution with higher quality obtained when Par_{OGN} = 5	Optimum design	Genetic algorithm with multi-populations ignoring neural network implementation	Hasancebi and et al. (2009b)
1	PIPST(1/2)	PIPST(3)	PIPST(3)	PIPST(3)	PIPST(2)
2	PIPST(1/2)	PIPST(3)	PIPST(3)	PIPST(3)	PIPST(3)
3	PIPST(1/2)	PIPST(3 1/2)	PIPST(3 1/2)	PIPST(6)	PIPST(4)
4	PIPST(1/2)	PIPST(3)	PIPST(3)	PIPST(3)	PIPST(3 1/2)
5	PIPST(1/2)	PIPST(3)	PIPST(3)	PIPST(3)	PIPST(3)
6	PIPST(1/2)	PIPST(3)	PIPST(3)	PIPST(3)	PIPST(3)
7	PIPST(1/2)	PIPST(8)	PIPST(2 1/2)	PIPDEST(4)	PIPST(3)
8	PIPST(1/2)	PIPST(2 1/2)	PIPST(2 1/2)	PIPDEST(2 1/2)	PIPST(2 1/2)
9	PIPST(1/2)	PIPST(3)	PIPST(3)	PIPST(3)	PIPST(3)
10	PIPST(1/2)	PIPST(2 1/2)	PIPST(2 1/2)	PIPDEST(2 1/2)	PIPST(3)
11	PIPST(1/2)	PIPST(6)	PIPST(2 1/2)	PIPST(2 1/2)	PIPST(2 1/2)
12	PIPST(1/2)	PIPST(5)	PIPST(2 1/2)	PIPST(2 1/2)	PIPST(2 1/2)
13	PIPST(1/2)	PIPDEST(6)	PIPST(2 1/2)	PIPST(5)	PIPST(2 1/2)
14	PIPST(1/2)	PIPST(3)	PIPST(3)	PIPST(3)	PIPST(2 1/2)
15	PIPST(1/2)	PIPST(2 1/2)	PIPST(2 1/2)	PIPST(2 1/2)	PIPST(2 1/2)
16	PIPST(1/2)	PIPST(3)	PIPST(2)	PIPST(6)	PIPST(2 1/2)
17	PIPST(1/2)	PIPST(2)	PIPST(2)	PIPST(6)	PIPST(2 1/2)
18	PIPST(1/2)	PIPST(2)	PIPST(2)	PIPST(10)	PIPEST(2)
19	PIPST(1/2)	PIPST(2)	PIPST(2)	PIPDEST(8)	PIPEST(2)
20	PIPST(1/2)	PIPST(2)	PIPST(2)	PIPST(2)	PIPST(2)
21	PIPST(1/2)	PIPST(2)	PIPST(2 1/2)	PIPDEST(4)	PIPST(2)
22	PIPST(1/2)	PIPEST(2)	PIPEST(2)	PIPST(5)	PIPST(2)
23	-	-	PIPST(3)	-	-
No. of penalized joint	546	0	0	0	0
No. of penalized element	354	0	0	0	5[a]
Weight	19444.239 N (4371.239 lbf)	221885.830 N (49881.919 lbf)	141613.912 N (31836.074 lbf)	275584.677 N (61953.9 lbf)	144753.999 N (32541.993 lbf)
Maximum weight	-	342013.217[b] N (76887.629 lbf)		342013.217[b] N (76887.629 lbf)	N/A
Average weight	-	208115.381 N (46786.198 lbf)		301689.478 N (67822.492 lbf)	N/A

a: Penalized due to the application of severe constraints; b: Obtained by use of design variables corresponding to the worst feasible solution.

strategy is not activated because any stagnation in genetic search does not exist. However, the neural network implementation achieves to adopt the parameters of genetic operators (Par_{All}) for an exploitation of current valuable genetic material for next generations (Table 3). This success is seen from the more converged results of EGAwMP compared to the approach proposed by Kaveh and Talatahari (2010) (Table 4). Although, the number of feasible solution (*NFS* = 2838 and 4494) obtained by Case I and II are lower compared to Case II (*NFS* = 119 + 129 + 177 +

Table 3. Statistical values of optimal designs according to topology design variables (horizontal and vertical division numbers) (a sphere-shaped dome structure with a fixed radius of R = 20 m [787.101 in)].

Shape design variables of sphere	Cases	Statistical values of feasible solutions obtained		Hor = 2 Ver = 2	Hor = 2 Ver = 3	Hor = 2 Ver = 4	Hor = 3 Ver = 2	Hor = 3 Ver = 3	Hor = 3 Ver = 4	Hor = 4 Ver = 2	Hor = 4 Ver = 3	Hor = 4 Ver = 4
R = 20 m (787.101 in)	Case I	NFS		24	29	40	143	216	226	864	1296	1312
		Vol. (m^3)	Max.	2.507	3.326	4.106	3.453	4.338	5.149	4.368	5.313	6.147
			Min.	1.373	1.715	2.057	1.732	1.898	2.253	2.147	2.324	2.689
			Aver.	1.934	2.539	3.011	2.592	3.126	3.710	3.256	3.828	4.429
	Case II	NFS		119	129	177	430	1194	1329	715	1500	1963
		Vol. (m^3)	Max.	3.909	4.666	6.088	5.574	6.654	7.813	7.203	8.302	9.471
			Min.	2.439	2.917	3.429	3.860	4.441	5.267	5.265	6.030	6.733
			Aver.	3.163	3.888	4.777	4.698	5.577	6.487	6.137	7.128	8.039
	Case III	NFS		60	61	62	300	354	359	1094	1057	1147
		Vol. (m^3)	Max.	2.507	3.326	4.106	3.453	4.338	5.149	4.151	5.033	5.758
			Min.	1.373	1.870	2.349	2.140	2.689	3.191	2.707	3.456	3.810
			Aver.	1.934	2.582	3.208	2.783	3.494	4.139	3.428	4.172	4.818

Vol: volume, NFS: number of feasible solutions, Hor: horizontal division number, Ver: vertical division number.

Table 4. The values of size and shape design variables corresponding to optimal designs (a sphere-shaped dome structure with a fixed radius of R = 20 m [787.101 in].

Parameter				Shape and size design variable values according to design approaches			
				Case I	Case II	Case III	Kaveh and Talatahari (2010)
SHDV	R = 20 m (787.101 in)	SIDV	SIDV1	PIPST(8)	PIPST(8)	PIPST(8)	-
			SIDV2	PIPST(10)	PIPST(10)	PIPST(10)	-
			SIDV3	PIPST(10)	-	PIPST(10)	-
			SIDV4	-	-	PIPST(12)	-
SHDV	R = 20 m (787.101 in)	R		20 m (787.101 in)	20 m (787.101 in)	20 m (787.101 in)	20 m (787.101 in)
Hor				2	2	2	-
Ver				2	2	2	-
SHDV	R = 20 m (787.101 in)	Optimal volume		1.373 m^3 (83785.600 in^3)	2.439 m^3 (148836.911 in^3)	1.373 m^3 (83785.600 in^3)	1.94 m^3 (118386.063 in^3)

SHDV: Shape design variables; SIDV: size design variables; Hor: horizontal division number; Ver: vertical division number.

Table 5. Statistical values of optimal designs according to topology design variables (horizontal and vertical division numbers) [a sphere-shaped dome structure with varying radius (R)].

Shape design variables sphere	Design approaches	Statistical values of feasible solutions obtained		Hor = 2 Ver = 2	Hor = 2 Ver = 3	Hor = 2 Ver = 4	Hor = 3 Ver = 2	Hor = 3 Ver = 3	Hor = 3 Ver = 4	Hor = 4 Ver = 2	Hor = 4 Ver = 3	Hor = 4 Ver = 4
(19.56 m < R < 20.32 m); (770 in < R < 800 in)	Case I	NFS		196	249	155	191	353	311	80	230	159
		Vol. (m^3)	Max.	1.921	2.568	3.153	2.666	3.223	3.966	3.198	3.985	4.461
			Min.	1.343	1.681	2.144	1.598	1.755	1.469	2.041	1.750	1.904
			Aver.	1.564	2.031	2.529	2.051	2.404	2.584	2.570	2.690	3.060
	Case II	NFS		12	21	10	4	68	117	1	48	64
		Vol. (m^3)	Max.	2.869	3.393	4.447	3.711	4.723	5.341	4.886	5.527	7.065
			Min.	2.430	2.716	3.015	3.459	3.179	3.128	4.886	3.984	4.005
			Aver.	2.609	2.973	3.580	3.586	4.016	4.436	4.886	4.927	5.370
	Case III	NFS		76	114	56	206	328	314	75	221	153
		Vol. (m^3)	Max.	1.931	2.500	2.948	2.504	3.150	3.618	3.042	3.549	3.976
			Min.	1.344	1.679	2.148	1.488	1.640	1.468	1.948	1.921	2.155
			Aver.	1.612	2.058	2.532	1.970	2.310	2.524	2.459	2.735	3.063
(10.16 m < R < 20.32 m); (400 in < R < 800 in)	Case I	NFS		437	493	262	396	605	310	196	287	152
		Vol. (m^3)	Max.	1.858	2.569	3.017	2.427	2.953	3.577	2.995	3.447	4.095
			Min.	0.371	0.492	0.607	0.565	0.699	0.839	0.725	0.890	1.170
			Aver.	0.976	1.310	1.584	1.309	1.627	1.893	1.583	1.949	2.317
	Case II	NFS		210	282	171	178	344	231	85	187	135
		Vol. (m^3)	Max.	2.605	3.253	4.089	3.781	4.568	5.392	4.232	5.591	6.433
			Min.	0.625	1.011	1.190	1.022	1.395	1.572	1.526	1.950	2.020
			Aver.	1.387	1.779	2.122	1.904	2.595	3.073	2.481	3.229	3.782
	Case III	NFS		375	364	193	398	595	326	196	341	170
		Vol. (m^3)	Max.	1.742	2.380	2.778	2.378	2.794	3.228	2.648	3.336	4.043
			Min.	0.376	0.528	0.651	0.636	0.764	0.979	0.789	1.063	1.155
			Aver.	0.928	1.195	1.501	1.244	1.624	1.951	1.541	2.005	2.297

Vol: volume, NFS: number of feasible solutions, Hor: horizontal division number and Ver: vertical division number.

430 + 1194 + 1329 + 715 + 1500 + 1963 = 7556) (Table 3).

The unity values of their members and the displacement values of their joints are depicted for optimal designs (Figure 10). Furthermore, the corresponding member and joint numbers are schematized in Figure 11a for Case I and III, and Figure 11b for Case II. Considering Table 4, the success of EGAwMP is shown with the lowest entire volume of dome structure with a fixed radius of 20 m (787.101 in), 1.373 m^3 (83785.600 in^3) compared to 2.439 m^3 (148836.911 in^3) and

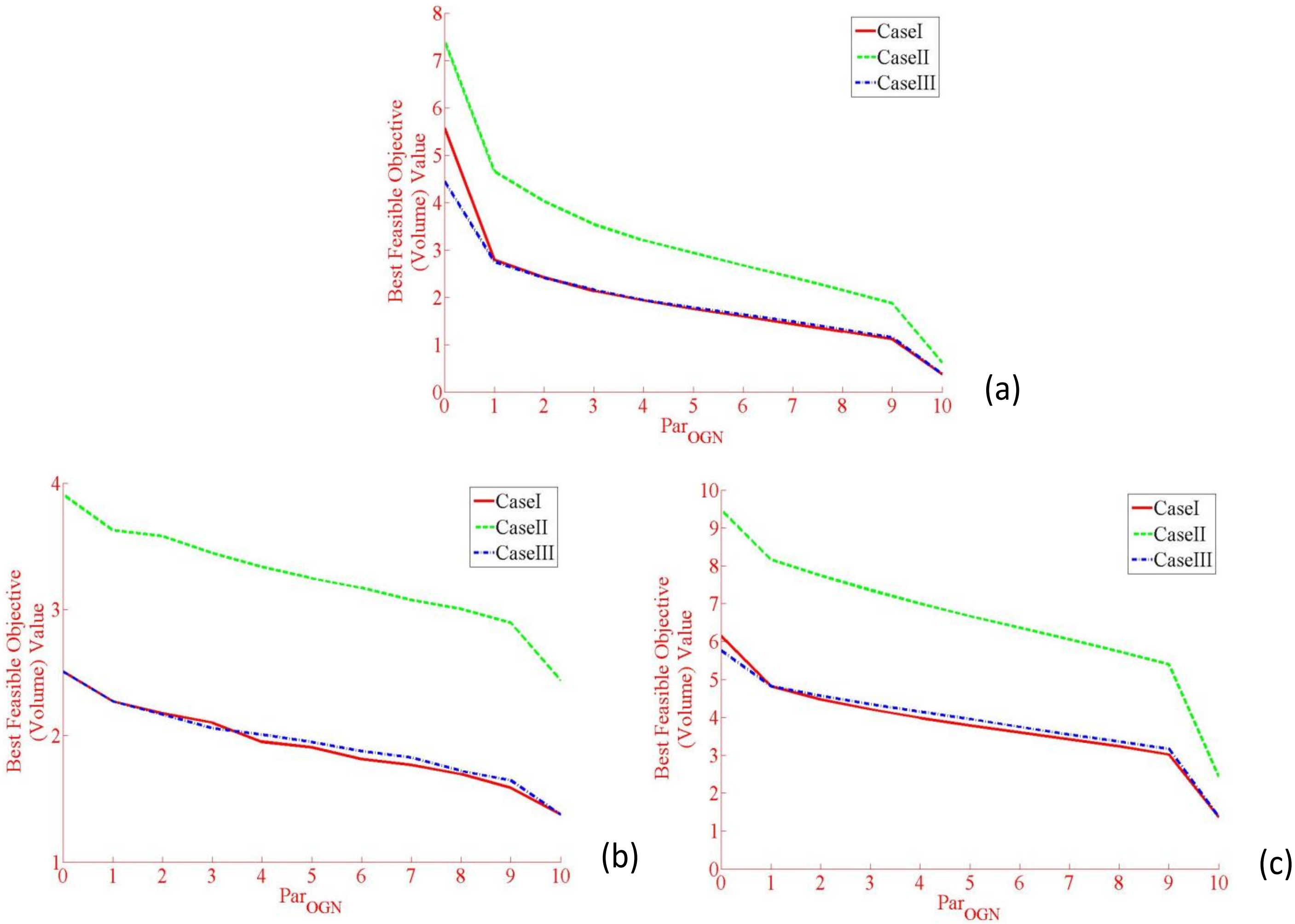

Figure 9. Convergence History of Genetic Search for Sphere-shaped Dome Structure Obtained by Use of Size Related Design Variable: R = 20 m (787.101 in) (a), 19.56 m < R < 20.32 m (770 in < R < 800 in) (b), and 10.16 m < R < 20.32 m (400 in < R < 800 in) (c).

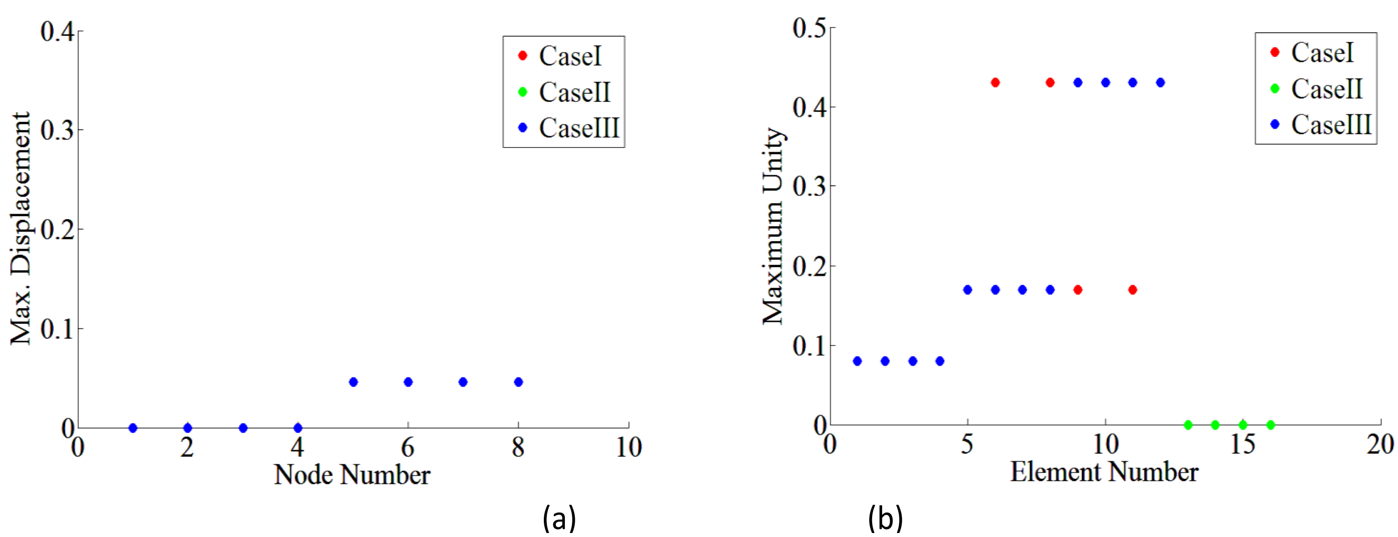

Figure 10. Maximum displacements and Unity_Max vlaues corresponding to optimum design (a-b) (A dome structure with varying size-shape-topology).

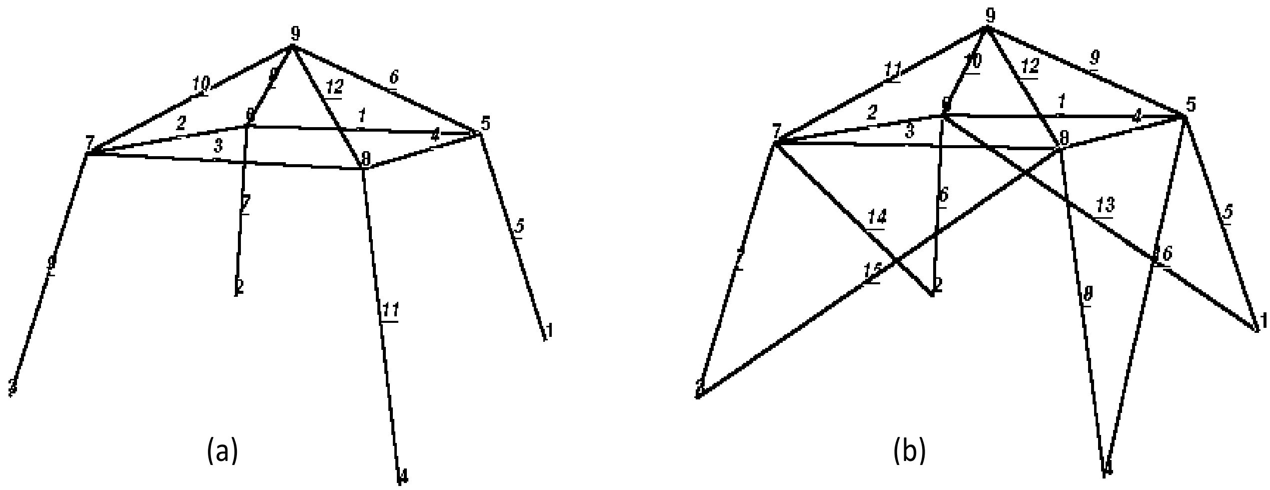

Figure 11. Member and Joint Coding Scheme of Optimum Design Obtained by CaseI III (a) and II (b) Using The Shape-related Design Variable as R = 20 m (787.101 in) (Table 5).

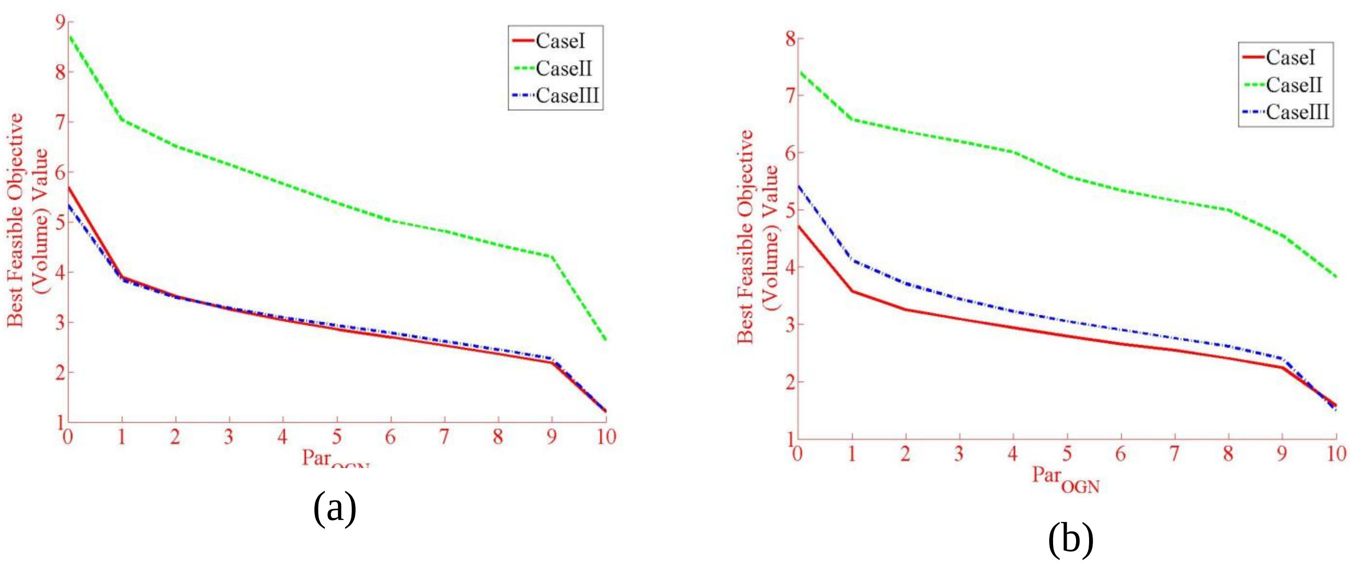

Figure 12. Convergence history of genetic search for ellipse-shaped dome structure obtained by use of size related design variable: 19.56 m < R < 20.32 m (770 in < R < 800 in) (a) and 10.16 m < R < 20.32 m (400 in < R < 800 in) (b).

1.94 m^3 (118386.063 in^3) obtained by usage of geometrical configuration represented by Case II and Kaveh and Talatahari (2010). Following the usage of a fixed parameter value of shape design variable [R = 20 m (787.101 in.)], the design of same sphere-shaped dome structure is optimized utilizing varying shape design variables. The statistical data and design variables of optimal designs are tabulated in Tables 5 and 6. EGAwMP is also successful to decrease the entire volume of sphere-shaped dome structure from 1.373 m^3 (83785.600 in^3), 2.439 m^3 (148836.911 in^3) and 1.373 m^3 (83785.600 in^3) to 1.343 m^3 (81984.764 in^3), 2.430 (148296.428 in^3) and 1.344 m^3 (82066.549 in^3) for Case I, II and III, respectively; thereby altering the radius (R) of dome structure within upper and lower limits 19.56 m (770 in) and 20.32 m (800 in). The success of EGAwMP with respect to big variation in radius (R) of dome structure within upper and lower limits 10.16 m (400 in) and 20.32 m (800 in) is also proven by a decrease in the entire volume of dome structure from 1.343 m^3 (81984.764 in^3), 2.430 (148296.428 in^3) and 1.344 m^3 (82066.549 in^3) to 0.371 m^3 (22639.809 in^3), 0.625 m^3 (38169.307 in^3) and 0.376 m^3 (22978.796 in^3) for Case I, II and III respectively (Table 6).

Table 6. The values of size and shape design variables corresponding to optimal designs [a sphere-shaped dome structure with varying radius (r)].

Parameter				Shape and size design variable values according to design approaches		
				Case I	Case II	Case III
SHDV	(19.56 m < R < 20.32 m); (770 in < R < 800 in)	SIDV	SIDV1	PIPST(8)	PIPST(8)	PIPST(8)
			SIDV2	PIPST(10)	PIPST(10)	PIPST(10)
			SIDV3	-	PIPST(10)	PIPST(10)
			SIDV4	-	PIPST(12)	-
	(10.16 m < R < 20.32 m); (400 in < R < 800 in)		SIDV1	PIPST(6)	PIPST(6)	PIPST(6)
			SIDV2	PIPST(6)	PIPST(6)	PIPST(6)
			SIDV3	-	PIPST(6)	PIPST(6)
			SIDV4	-	PIPST(6)	-
SHDV	(19.56 m < R < 20.32 m); (770 in < R < 800 in)	R		19.58 m (770.811 in)	19.92 m (784.420 in)	19.59 m (770.849 in)
	(10.16 m < R < 20.32 m); (400 in < R < 800 in)	R		10.18 m (400.923 in)	11.01 m (433.491 in)	10.33 m (406.806 in)
Hor				2	2	2
Ver				2	2	2
SHDV	(19.56 m < R < 20.32 m); (770 in < R < 800 in)	Optimal volume		1.343 m^3 (81984.764 in^3)	2.430 (148296.428 in^3)	1.344 m^3 (82066.549 in^3)
	(10.16 m < R < 20.32 m); (400 in < R < 800 in)			0.371 m^3 (22639.809 in^3)	0.625 m^3 (38169.307 in^3)	0.376 m^3 (22978.796 in^3)

SHDV: shape design variables, SIDV: size design variables, Hor: horizontal division number and Ver: vertical division number.

Table 7. Statistical values of optimal designs according to topology design variables (horizontal and vertical division numbers) [an ellipse-shaped dome structure with varying parameters of shape design variables (A, B and C)].

Shape design variables of ellipse	Design approaches	Statistical values of feasible solutions obtained		Hor = 2 Ver = 2	Hor = 2 Ver = 3	Hor = 2 Ver = 4	Hor = 3 Ver = 2	Hor = 3 Ver = 3	Hor = 3 Ver = 4	Hor = 4 Ver = 2	Hor = 4 Ver = 3	Hor = 4 Ver = 4
Set 1	Case I	NFS		131	377	207	112	398	317	63	287	166
		Vol. (m^3)	Max.	1.994	2.668	3.276	2.765	3.477	4.019	3.343	4.128	4.715
			Min.	1.576	1.862	2.340	2.133	2.324	2.253	2.437	2.605	2.732
			Aver.	1.752	2.194	2.706	2.415	2.792	3.028	2.861	3.258	3.567

Table 7. Contd.

	Case II	NFS		-	-	24	-	1	53	-	6	60
		Vol. (m^3)	Max.	-	-	4.598	-	4.852	6.073	-	6.654	7.424
			Min.	-	-	3.880	-	4.852	4.394	-	5.444	5.822
			Aver.	-	-	4.231	-	4.852	5.256	-	5.8955	6.407
	Case III	NFS		72	235	119	78	317	339	65	290	161
		Vol. (m^3)	Max.	2.008	2.615	3.264	2.663	3.275	3.969	3.205	4.015	4.449
			Min.	1.488	1.868	2.369	2.106	2.056	2.302	2.408	2.592	2.851
			Aver.	1.724	2.147	2.720	2.342	2.634	3.020	2.797	3.192	3.637
Set 2	Case I	NFS		191	393	199	214	505	275	89	311	160
		Vol. (m^3)	Max.	1.943	2.625	3.108	2.607	3.381	3.976	3.418	3.993	4.518
			Min.	1.206	1.566	1.955	1.835	1.735	1.980	2.324	2.224	2.473
			Aver.	1.573	2.010	2.455	2.197	2.495	2.825	2.781	3.017	3.452
	Case II	NFS		-	29	56	-	47	127	-	17	62
		Vol. (m^3)	Max.	-	3.427	4.731	-	4.857	5.805	-	6.040	7.075
			Min.	-	2.624	2.782	-	3.651	3.771	-	4.919	5.227
			Aver.	-	3.024	3.593	-	4.363	4.798	-	5.552	6.046
	Case III	NFS		140	294	159	119	520	359	62	319	172
		Vol. (m^3)	Max.	2.004	2.493	3.126	2.469	3.276	3.804	3.243	3.828	4.219
			Min.	1.204	1.455	1.785	1.722	1.764	2.120	2.202	2.346	2.716
			Aver.	1.538	1.947	2.336	2.126	2.456	2.840	2.653	3.041	3.430

Set 1:	Set 2:
19.56 m. < A < 20.32 m (770 in. < A < 800 in.)	19.56 m. < A < 20.32 m (770 in. < A < 800 in.)
20.32 m. < B < 21.59 m (800 in. < B < 850 in.)	20.32 m. < B < 21.59 m (800 in. < B < 850 in.)
19.56 m. < C < 20.32 m (770 in. < C < 800 in.)	10.16 m. < C < 20.32 m (400 in. < C < 800 in.)

Vol: volume, NFS: number of feasible solutions, Hor: horizontal division number, Ver: vertical division number.

According to optimal volume values, the sphere-shaped dome configuration represented by Case I leads to the most convergence degree in entire volume by decreasing entire volume from 1.343 m^3 (81984.764 in^3) to 0.371 m^3 (22639.809 in^3) (Table 6). Furthermore, the

Table 8. The values of size and shape design variables corresponding to optimal designs [(an ellipse-shaped dome structure with varying parameters of shape design variables (A, B and C)].

Parameter				**Size and shape design variable values according to design approaches**		
				Case I	**Case II**	**Case III**
SHDV	SHDV set 1	SIDV	SIDV1	PIPST(6)	PIPST(6)	PIPST(6)
			SIDV2	PIPST(10)	PIPST(8)	PIPST(10)
			SIDV3	-	PIPST(8)	PIPST(8)
			SIDV4	-	PIPST(10)	-
	SHDV set 2		SIDV1	PIPST(6)	PIPST(6)	PIPST(6)
			SIDV2	PIPST(8)	PIPST(6)	PIPST(6)
			SIDV3	-	PIPST(8)	PIPST(8)
			SIDV4	-	PIPST(10)	-
SHDV	SHDV set 1	A		19.69 m (775.227 in)	20.03 m (788.559 in)	20.09 m (790.909 in)
		B		20.35 m (801.472 in)	20.59 m (810.638 in)	20.80 m (818.954 in)
		C		19.58 m (770.909 in)	19.88 m (782.785 in)	19.56 m (770.160 in)
	SHDV set 2	A		19.64 m (773.532 in)	20.03 m (788.721 in)	19.87 m (782.214 in)
		B		20.36 m (801.591 in)	20.39 m (802.942 in)	20.35 m (801.372 in)
		C		12.42 m (489.278 in)	12.52 m (493.026 in)	12.07 m (475.266 in)
Hor				2	2	2
Ver				2	3	2
SHDV	SHDV set1	Optimal volume		1.576 m^3 (96173.420 in^3)	3.88 m^3 (236804.256 in^3)	1.488 m^3 (90849.618 in^3)
	SHDV set2			1.206 m^3 (73594.635 in^3)	2.624 m^3 (160126.304 in^3)	1.204 m^3 (73472.587 in^3)

SHDV set1:
19.56 m. < A < 20.32 m (770 in. < A < 800 in.)
20.32 m. < B < 21.59 m (800 in. < B < 850 in.)
19.56 m. < C < 20.32 m (770 in. < C < 800 in.)

SHDV set2:
19.56 m. < A < 20.32 m (770 in. < A < 800 in.)
20.32 m. < B < 21.59 m (800 in. < B < 850 in.)
10.16 m. < C < 20.32 m (400 in. < C < 800 in.)

SHDV: shape design variables, SIDV: size design variables, Hor: horizontal division number and Ver: vertical division number.

effect of ellipse-shaped dome structure on the convergence degree of optimal designs is also investigated. Therefore, fitness value-related statistical data and values of design variables are tabulated in Tables 7 and 8. EGAwMP achieves to minimize the entire volume of ellipse-shaped dome structure with varying parameters of shape design variables (A, B and C) to the smallest value 1.488 m^3 (90849.618 in^3) compared to 1.576 m^3 (96173.420 in^3) and 3.88 m^3 (236804.256 in^3) obtained by use of geometrical configurations represented by Case I and II (Table 8). Furthermore, EGAwMP is also executed for design optimization of ellipse-shaped dome structure using decreased values of shape design variables (A, B and C) and proven its success with a decrease in the entire volume of dome structure from 1.576 m^3 (96173.420 in^3), 3.88 m^3 (236804.256 in^3) and 1.488 m^3 (90849.618 in^3) to 1.206 m^3 (73594.635 in^3), 2.624 m^3 (160126.304 in^3) and 1.204 m^3 (73472.587 in^3) for Case I, II and III. Particularly, it is obvious that usage of geometrical configuration represented by Case III is resulted with an optimal design with most converged degree.

FINAL REMARKS

In this study, a traditional genetic algorithm methodology integrated with multiple populations is enhanced by an implementation of neural network and a new design strategy. The enhanced genetic algorithm methodology named EGAwMP is proposed to optimize the design of dome structures, while the implementation of neural network is used to adopt both parameter values of genetic operator and design variables, a stagnation problem arisen in any evolving generation of genetic search is overcome by the new design strategy based on provisions of LRFD_AISC V3 specification. Furthermore, in order to improve the convergence degree of optimal designs, topology and shape design variables along with size design variables are coded into the chromosomes of individuals. In this regard, the varying lengths of chromosomes are adopted by use of a new technique named multi-started genetic search to properly execute the optimization procedures of EGAwMP. The computational performance of EGAwMP is evaluated by two application examples. Furthermore, one of these examples is used to investigate the effect of using varying shape and topology design variables on the convergence degree of optimal designs. Also, this effect is investigated for design optimization of both ellipse and sphere-shaped dome structure. According to optimal designs obtained by EGAwMP and the other optimization approaches in literature, it is demonstrated as:

i) EGAwMP has a better computational capacity thereby obtaining more converged optimal designs than the other existing optimization approaches.
ii) EGAwMP succeed in increasing the convergence degree of its optimal designs by activating both the proposed design strategy and neural network implementation.
iii) An inclusion of shape and topology design variables along with size design variables into optimization procedures of EGAwMP leads to an increase in the quality degree of optimal designs.
iv) Constructing the dome structure using a sphere-shaped template rather than ellipse-shaped one leads to a reduction in its volume.
v) The inclusion of diagonal member to optimization procedures of EGAwMP causes a reduction in the converged degree of optimal designs. Particularly, using only size design variables along with decreased topology design variables, vertical and horizontal division numbers leads to an increase in the quality degree of optimal designs.
vi) Reducing the parameter values of both shape and topology design variables also elevates the quality degree of optimal designs.

Nomenclature: $\mathbf{A_g}$**,** Gross cross sectional area; **λ,** slenderness parameter; $\mathbf{F_y}$**,** yield stress; **S,** elastic section modules; $\mathbf{F_{cr}}$**,** critical stress; $\mathbf{M_n}$**,** nominal flexural strength; **K,** effective length factor; $\mathbf{M_r}$**,** limiting buckling moment; **L,** Un-braced member length; $\mathbf{M_p}$**,** plastic bending moment; **Q,** reduction factor; $\mathbf{P_n}$**,** nominal axial strength; **h,** clear distance; $\mathbf{C_b}$**,** bending coefficient; $\mathbf{A_w}$**,** area of web; $\mathbf{C_w}$**,** warping coefficient; t, plate thickness; $\mathbf{V_n}$**,** nominal shear strength; **b,** plate width.

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APPENDIX

Design requirements of skeleton steel structures with rolled beams

While nominal axial tension strength $P_n^{tension}$ is governed by Equation A1, nominal axial compression strength $P_n^{compression}$ is determined based on limit states of flexural buckling (Equation A2). Nominal flexural strength M_n varies depending on build-up member bent about their major axis. Thus, M_n is the lower value obtained according to the limit states of yielding, lateral-torsional buckling, flange and web buckling (Equations A3 to A6). Also, nominal shear strength is computed using Equation A7. Furthermore, nominal strength parameters are presented in Table A-F1-1 in manual of AISC_LRFD V3. Nominal Axial Tension Strength (D1-1) for $P_n^{tension}$ in manual of AISC_LRFD V3:

$$P_n^{tension} = F_y * A_g \qquad \text{(A1)}$$

Nominal Axial Compressive Strength (E2-1) for $P_n^{compression}$, A-B5-15, A-B5-16 for F_{cr}, [Q for A-B5-17, A-B5-12, A-B5-5, A-B5-6]

$$P_n^{compression} = A_g F_{cr} \qquad \text{(A2)}$$

Nominal Flexural Strength, Min ($M_n^{Yielding}$, $M_n^{Lateral\ Torional\ Buckling}$, $M_n^{Flange\ Local\ Buckling}$, $M_n^{Web\ Local\ Buckling}$); Yielding (F1-1) for $M_n^{Yielding}$

$$M_n^{yielding} = F_y * S \qquad \text{(A3)}$$

Flange local buckling (A-F1-1)-(A-F1-4) for $M_n^{FlangeLocalBuckling}$

$$M_n^{Flange\ Local\ Buckling} = \begin{cases} F_y * Z_z & \text{if } \lambda < \lambda_p \\ M_p - (M_p - M_r) * (\dfrac{\lambda - \lambda_p}{\lambda_r - \lambda_p}) & \text{if } \lambda_p < \lambda \le \lambda_r \\ S_z * F_{cr} & \text{if } \lambda > \lambda_r \end{cases} \qquad \text{(A4)}$$

Lateral Torsional Buckling (F1-2)-(F1-16) for $M_n^{LateralTorsionalBuckling}$

$$M_n^{Lateral\ Torional\ Buckling} = \begin{cases} M_p & \text{if } \lambda \le \lambda_p \\ C_b * (M_p - (M_p - M_r) * (\dfrac{\lambda - \lambda_p}{\lambda_r - \lambda_p})) & \text{if } \lambda_p < \lambda \le \lambda_r \\ S_z * F_{cr} \le F_y * Z_z & \text{if } \lambda > \lambda_r \end{cases} \qquad \text{(A5)}$$

Web-Local Buckling (A-F1-3) for $M_n^{WebLocalBuckling}$

$$M_n^{Web\ Local\ Buckling} = \begin{cases} F_y * Z_z & \text{if } \lambda \le \lambda_p \\ M_p - (M_p - M_r) * (\dfrac{\lambda - \lambda_p}{\lambda_r - \lambda_p})) & \text{if } \lambda_p < \lambda \le \lambda_r \end{cases} \qquad \text{(A6)}$$

Nominal Shear Strength (F2-1), (F2-3) or (A-F2-1) ile (A-F2-3) for V_n

$$V_n = \begin{cases} 0.60 * A_y * F_y & \text{if } \frac{h}{t_w} \le 2.45 * \sqrt{\frac{E}{F_y}} \\ 0.60 * A_y * F_y * \frac{2.45 * \sqrt{\frac{E}{F_y}}}{\frac{h}{t_w}} & \text{if } 2.45 * \sqrt{\frac{E}{F_y}} < \frac{h}{t_w} \le 3.07 * \sqrt{\frac{E}{F_y}} \\ \frac{4.52 * E * A_y}{(\frac{h}{t_w})^2} & \text{if } \frac{h}{t_w} > 3.07 * \sqrt{\frac{E}{F_y}} \end{cases} \qquad \text{(A7)}$$