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Practical optimization of power transmission towers using the RBF-based ABC algorithm

Faezeh Taheri[1a], Mohammad Reza Ghasemi*[1] and Babak Dizangian[2b]

[1]Department of Civil Engineering, University of Sistan and Baluchestan, Zahedan, Iran
[2]Department of Civil Engineering, Velayat University, Iranshahr, Iran

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Abstract. This paper is aimed to address a simultaneous optimization of the size, shape, and topology of steel lattice towers through a combination of the radial basis function (RBF) neural networks and the artificial bee colony (ABC) metaheuristic algorithm to reduce the computational time because mere metaheuristic optimization algorithms require much time for calculations. To verify the results, use has been made of the CIGRÉ Tower and a 132 kV transmission towers as numerical examples both based on the design requirements of the ASCE10-97, and the size, shape, and topology have been optimized (in both cases) once by the RBF neural network and once by the MSTOWER analyzer. A comparison of the results shows that the neural network-based method has been able to yield acceptable results through much less computational time.

Keywords: optimization; power transmission towers; steel lattice towers; RBF neural network; artificial bee colony (ABC) algorithm

1. Introduction

A power transmission network makes use of wooden, concrete, and steel lattice towers, but the latter are used more due to their high strength-to-weight ratio (Tort *et al*. 2017). Transmission towers are truss structures responsible for a major part of the costs of the transmission line (Tort *et al*. 2017). Since a single transmission tower design is used several times in a transmission line, reducing its costs by optimization methods will greatly reduce the costs of the entire system (Souza *et al*. 2016). In recent decades, optimization in all fields of engineering has received much attention (Klansek *et al.* 2006, Yi *et al*. 2011, Lee *et al*. 2012, Yi *et al*. 2012, Fiouz *et al*. 2013, Dizangian and Ghasemi 2016, Yi *et al*. 2017, Ghiasia and Ghasemi 2018) and since the general objective in many civil optimization problems is to reduce the weight of the desired structure under specific loads and constraints, and hence lessen the related costs, reducing the costs of transmission towers will greatly affect the electrical industry.

Researches on the optimization of transmission towers include that of Rao (1995) who proposed an optimization method for the weight and geometry of high pressure transmission towers by studying a 400 kV double-circuit transmission tower under multiple-loading conditions. Using a reliability-based method, Natarjan and Santhakumar (1995) optimized the size and shape of transmission towers. Sheppard and Palmer (1972) used a dynamic method and examined the number of panels and bracing patterns that created a light design to optimize transmission towers. Using a hybrid method of determining the optimum shape, cross-section, and materials of the bar elements, Taniwaki and Ohkubo (2004) studied a 218-member tower and optimized a truss transmission tower exposed to static and seismic loads. Sivakumar *et al.* (2004) used a genetic algorithm with discrete variables to optimize steel lattice transmission towers and showed that their proposed method was quite acceptable for large-scale problems. Using a combination of a topology optimization method and a simulated annealing program, Shea *et al.* (2006) optimized the topology, shape, and size of transmission towers for the structure weight reduction using discrete variable and reduced the weight by 16.7%. Mathakari *et al.* (2007) performed the reliability-based optimization of the shape, topology, and size of transmission towers using multi-objective genetic algorithms under the wind load the pressure and direction of which were considered as random variables in the analyses. Proposing a GA with discrete variables, Guo and Li (2011) optimized the topology of high-voltage transmission towers through the TCO (topology combination optimization), LCO (layer combination optimization), CSSO (cross-section size optimization), and SCO (shape combination optimization) methods and showed that the first two methods performed better than the other two. Using multi-objective evolutionary algorithms, Noilublao and Bureerat (2011) simultaneously optimized the topology, shape, and size of 3D truss towers. Paris *et al.* (2010) used continuous and discrete variables and studied the optimization of the size and shape of the high-pressure transmission towers. Using the ASCE10-97, Souza *et al.* (2016) proposed a transmission tower optimization method where they optimized the size, size and shape, and size, shape, and

*Corresponding author, Ph.D., Professor
E-mail: mrghasemi@eng.usb.ac.ir
[a] M.Sc. Student
[b] Ph.D. Assistant Professor

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topology using the FA (firefly algorithm) and BSA (backtracking search algorithm) that resulted in a 4.6% reduction in the structure weight. Using the SA (simulated annealing) algorithm, Couceiro *et al.* (2016) optimized the size and shape of transmission towers with respectively continuous and discrete variables in one real and two standard problems and the results showed a 40% reduction in the structure weight.

Chunming *et al.* (2012) optimized the design of high voltage transmission towers using the NSGA-II (a genetic algorithm) where the elements' section areas and materials were the design variables, the transmission tower construction cost was the economic objective, and the minimum displacement of the control point was the structural optimization objective. Using a two-phase SA algorithm, the PLS-TOWER Software, and the ASCE10-97 Code, Tort *et al*. (2017) studied three 110, 220, and 400 kV transmission towers, optimized their sizes and shapes, and reduced their structure weights by about 10-26%. Kaveh and Ghazaan (2018) optimized three 47-, 160-, and 244-member steel lattice towers under multiple loads with discrete variables using the CBO, ECBO, VPS, and MDVC-UVPS algorithms and showed (by the comparison of the results) that the latter performed the best.

There are many stochastic optimization algorithms given significant attention to, in recent years. For the purpose of the present research, since the detailed analysis and design of transmission towers with all the in-depth construction remarks takes a considerable time efforts, its stochastic optimum design will obviously require a significant computational cost. Therefore, attempts were made to involve neural networks to substitute the analysis after being trained, as well as modifying the way in which constraints were handled in the ABC optimization algorithm, both of which were aimed to speed up the optimization process significantly. This paper aims to optimize the size, size and shape, and size, shape, and topology of steel lattice transmission towers using the MSTOWER Software (meant specifically for the analysis and design of transmission towers) to model, analyze, and design the primary tower. The optimization algorithm used in this research was first proposed by Karaboga (2005). It is a common metaheuristic algorithm called the artificial bee colony (ABC) and is inspired by the bees' food search behavior in the nature. In recent years, this algorithm, codified in the MATLAB Software, has been used as an optimization tool and has shown good performance (Karaboga and Basturk 2007, Sonmez 2011, Gao *et al.* 2012, Delgarm *et al.* 2016, Cui 2017). As mentioned before, this paper makes use of a combination of the RBF neural networks (that perform well in the approximation of functions) and the ABC algorithm to reduce the lengthy computational time. To compare the network-based results, optimization has also been done by the MSTOWER analyzer through linking it with the MATLAB code of the ABC algorithm and the results of the two optimization methods have been studied and compared. In this process, the design variables are of the discrete type and the member stress and slenderness are the design constraints. It is worth noting that the design requirements are based on the ASCE10-97 Code (2000) and the paper has been so organized as to describe the neural networks (and the RBF neural network) in Section 2, explain the general structure and formulation of the optimization problem in Section 3, define the optimization algorithm in Section 4, explain the two optimization methods used in this paper in Sections 5 and 6, present the numerical examples in Section 7, and provide the conclusions in Section 8.

2. Neural networks

Nowadays, neural networks are quite popular in many research field (Ghaboussi and Wu 1998, Qu *et al.* 2003, Yi et al. 2013). These networks have been inspired by the biological neural systems and process the information similar to the brain (Tang 2006, Saxena and Pathak 2015). Aimed to generate outputs based on the given inputs, neural networks have such many applications as classification (Hore *et al.* 2016, Chatterjee *et al.* 2017), pattern recognition, optimization, prediction (Cheng *et al*. 2007,Tan *et al.* 2017), system identification, modeling, and control (Poggio and Girosi 1990).

2.1 Radial basis function (RBF) neural network

RBF neural networks are capable of identifying different patterns in a short time. Giroussei and Poggi (1990) and also Hartmann and Kepler (1990) proved that the RBF neural networks are strong structural approximations (Schilling *et al.* 2001, Huang *et al.* 2005). Their overall structure consists of three layers: 1) the input layer, where there is no processing, is defined as a vector and contains the main data, 2) the invisible or hidden layer that provides a nonlinear conformity between the input layer and a usually larger-dimension space and plays an important role in converting nonlinear patterns to separable linear ones(Meng *et al.* 2010). The nonlinear function used in the hidden layer is mainly a Gaussian one Eq. (1) and its parameters include the center and the width.

$$\emptyset\left(\left\|x-u_j\right\|\right)=e^{\frac{-\left(\left\|x-u_j\right\|\right)}{\sigma_j}} \tag{1}$$

where x is the input columnar vector, u_j is the gravity vector related to the i^{th} neuron, σ_j is the width factor of the j^{th} kernel, and $\|\ \|$ shows the Euclidean distance.

First, each sample-center distance in the hidden layer is computed; it then passes the Gaussian function and enters the feature space. And, 3) the output layer where the data created in the new space are multiplied by the corresponding synapse weights and then added together linearly. The output of these networks is a linear combination of the RBFs for the input parameters and neurons. In general, the objective in RBF neural networks is to minimize Eq. (2):

$$f(x)=\sum_{i=1}^{m} w_i\emptyset_i(x) \tag{2}$$

where m is the number of the dimensions of the hidden layer and w is the synaptic weights.

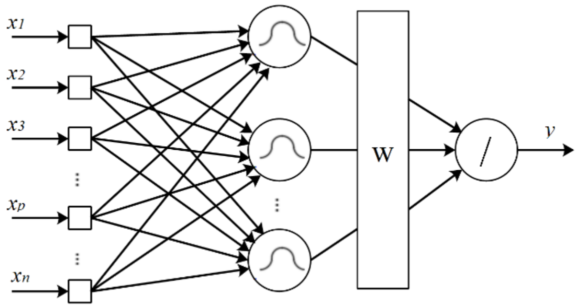


Fig. 1 General form of RBF neural networks

RBF neural networks are used in the function approximation, classification, prediction of time series, and system control, and their general form is as in Fig. 1.

To reduce the lengthy computational time, this paper makes use of a combination of the ABC algorithm and RBF neural networks that perform well in the functions approximation.

3. Optimization problem

In optimization problems (formulated as follows), the design variables are so calculated, under specific constraints, as the objective function (usually the cost in structural problems) may reach its lowest value:

$$optimize : min\ f(x)$$

$$subject\ to:$$

$$g_j(x) \leq 0\ ,\quad j = 1,2,\dots,n \tag{3}$$

$$h_i(x) = 0\ ,\quad i = 1,2,\dots,m$$

$$x_k^l \leq x_k \leq x_k^u\ ,k = 1,2,\dots,l$$

where *f(x)* is the objective function, *x* is a vector with *l* design variables, *g(x)* and *h(x)* are the equal and unequal constraints, x_k^l and x_k^u are respectively the upper and lower bounds of the design variables, and *n* and *m* are respectively the number of unequal and equal constraints. In this paper, the objective function Eq. (4) is the weight of the power transmission tower:

$$w = \rho \sum_{i=1}^{n_b} l_i A_i \tag{4}$$

where ρ is the density of the desired material, n_b is the number of elements of the transmission tower, and $l_i$and A_i are respectively the length and cross-sectional area of the i[th] member.

3.1 Design variables

In this paper, the size of the transmission tower is optimized by discrete design variables, being the elements' cross-sectional areas, selected from a European Angle Profile Catalog list arranged in an increasing order of the cross-section areas. They were considered as design variables for size optimization and were stored in vector A. The base width was regarded as the shape design variable and stored as Wb in the design variables vector. The width of the other panels was obtained using the angle and height of the tower body. Its topology is optimized by dividing the tower into small portions with specific shapes, heights, and widths called panels, are considered in some parts of the tower, as design variables for the topology optimization problem. Therefore, the number of variables in a tower topology design is equal to the number of panels selected to change their topology. These design variables are stored in vector P. Accordingly, the design vector for an arbitrary tower optimization problem, consisting of size, shape and topology variables, is presented in Eq. (5).

$$x = \{A_1, \dots, A_n, W_b, P_1, \dots, P_m\} \tag{5}$$

Where n and m are the number of cross sections and the number of topology changes of the panels, respectively.

3.2 Design constraints

In the transmission tower design, the members should be selected based on codes and so designed as to satisfy the constraints which, in this study, include the stress and slenderness Eqs. (6)-(7) and their allowable values are based on the ASCE10-97 Code (2000).

$$g_1(x) = \frac{\sigma_i}{\bar{\sigma}_i} - 1 \leq 0\ ,\quad i = 1,2,\dots,m \tag{6}$$

$$g_2(x) = \frac{\lambda_i}{\bar{\lambda}_i} - 1 \leq 0\ ,\quad i = 1,2,\dots,m \tag{7}$$

where σ_i and λ_i (with allowable values $\bar{\sigma}_i$ and $\bar{\lambda}_i$) are, respectively, the stress and slenderness in the i[th] member.

3.2.1 Members' compressive strength

A member compressive strength is, according to ASCE10-97 (2000), the product of A (cross-sectional area) and F_C (allowable compressive stress) shown in Eqs. (8)-(10):

$$P_C = F_C.A \tag{8}$$

$$F_C = \begin{cases} \left[1 - \frac{1}{2}\left(\frac{kl/r}{C_c}\right)^2\right] F_{cr} & if\ \frac{kl}{r} \leq C_c \\ \frac{\pi^2 E}{(kl/r)^2} & if\ \frac{kl}{r} > C_c \end{cases} \tag{9}$$

$$C_c = \pi\sqrt{2E/F_y} \tag{10}$$

where E is the steel elasticity modulus, k is the effective length coefficient, l is the member's unanchored length, r is the radius of gyration, C_c is the critical slenderness ratio, F_y is the yield stress, and F_{cr} is the critical stress found from Eq. (11):

$$F_{cr} = \begin{cases} F_y & \text{if } \frac{w}{t} \leq \frac{80\Psi}{\sqrt{F_y}} \\ \left[1.667\text{-}0.677\frac{w/t}{(w/t)_{min}}\right] F_y & \text{if } \frac{80\Psi}{\sqrt{F_y}} \leq \frac{w}{t} \leq \frac{144\Psi}{\sqrt{F_y}} \\ \frac{0.0332\pi^2 E}{(w/t)^2} & \text{if } \frac{w}{t} \geq \frac{144\Psi}{\sqrt{F_y}} \end{cases} \tag{11}$$

where $\Psi = 1$ and $\Psi = 2.62$ in the ksi unit for F_y and MPa, respectively.

3.2.2 Members' tensile strength

An axially loaded member's tensile strength (Eq. (12)) is F_t (tensile stress) × A_{net} (net section area) where $A_{net} = A_{eff}$ (effective section area) – area of holes in the section.

$$P_t = F_t . A_{net} \tag{12}$$

$$F_t = \begin{cases} F_y & \text{if connected by both legs} \\ 0.90 F_y & \text{if connected by single leg} \end{cases} \tag{13}$$

$$A_{net} = A_{eff} - h.t.n_h \tag{14}$$

$$A_{eff} = \begin{cases} A & \text{if connected by both legs or long leg only} \\ A-(b-a).t.n_b & \text{if connected by short leg only} \end{cases} \tag{15}$$

3.2.3 Maximum slenderness ratio

Slenderness limits for the leg and redundant members are not to exceed the following values:

$$\lambda_{max} = \left(\frac{kl}{r}\right)_{max} = \begin{cases} 150 & \text{for leg members} \\ 200 & \text{for other members} \\ 250 & \text{for redundant members} \end{cases} \tag{16}$$

3.3 Penalty function

A highly applicable method of converting a constrained to unconstrained optimization problem is to make use of the penalty function where each constraint is first normalized by dividing it by its allowable value and then fined according to how much it has violated each objective function constraint; *p(x)* (penalty function) and *f(x)* (modified objective function) are as follows:

$$P(x) = \sum_{i=1}^{m} (max\left(\frac{g_i(x)}{\bar{g}_i(x)} - 1{,}0\right))^2 \tag{17}$$

$$f(x) = w(x) + r_p \times P \tag{18}$$

where *f(X)* is the modified objective function and *P* and r_p are the penalty function and the related coefficient; in this research, the value of r_p varies in each iter and is found by Eq. (19):

$$r_p = max\left(100{,}20 \times \left(1 + 0.02 \times (iter - 1)\right)\right) \tag{19}$$

In this paper, the origin of the penalization approach was extracted from the book by Belegundu and Chandrupatla (2014). However, a slight change was implemented within the penalization approach, allowing for more restraint to any violation of constraints as further going along the optimization procedure iteratively. This is to ensure a non-penalized optimum solution at the end of the process, while avoiding any premature convergence at the early stages of the process.

4. ABC optimization algorithm

In the last few decades, metaheuristic algorithms have found a special place in engineering problems. One example is the artificial bee colony (ABC) algorithm which is based on the honey bees' collective intelligence and clever behavior and is used in the constrained and unconstrained optimization problems. Inspired by the bees' food-search behavior in the nature, the ABC algorithm was first presented by Karaboga (2005) as an optimization method. In this algorithm, bees are divided into three categories: 1) employed bees that discover a source and bring food from it, 2) onlooker bees that stay inside the hive and watch the employed bees to find food supplies by dancing, and 3) scout bees that search for food randomly around the hive.

4.1 Steps in the ABC algorithm

The ABC algorithm contains 4 main steps as follows:

Step 1 – Initialization: here, the problem objective function and required parameters are determined; the vector of the input parameters is defined according to Eq. (20):

$$x_i = \{x_{i1}, x_{i2}, \ldots, x_{iD}\} \quad i = 1,2,\ldots,SN \tag{20}$$

where *D* is the number of the problem design variables and *SN* is the bees' population number.

Next, each design variable is selected randomly between its upper and lower bounds Eq. (21).

$$X_{ij} = x_{min\,j} + rand[0,1] \times \left(x_{max\,j} - x_{min\,j}\right), \quad j = 1,2,\ldots,D \quad i = 1,2,\ldots,SN \tag{21}$$

Step 2 – Employed bees: here, the employed bees search for a better food source around the food source at point X_{ij}; Eq. (22) is used to determine the new food source.

$$V_{ij} = x_{ij} + \varphi_{ij}\left(x_{ij} - x_{kj}\right) \quad j \epsilon \{1,2,\ldots,D\}, k \epsilon \{1,2,\ldots,SN\} \wedge k \neq j \tag{22}$$

where V_{ij} is the new position vector, *k* is a random number, and $\boldsymbol{\varphi}_{ij}$ is another random number with a uniform distribution in the [-1, 1] interval. After determining the new position, its fitness level is found from Eq. (23):

$$fit_i = \begin{cases} \dfrac{1}{1+f_i} & if\ f_i > 0 \\ 1 + abs(f_i) & if\ f_i \leq 0 \end{cases} \tag{23}$$

Step 3 – Onlooker bees: here, the employed bees become onlooker bees after returning to the hive and start searching, with a specified probability, around one of the points found by the employed bees. Onlooker bees do their selection based on the probabilities calculated by the employed bees through Eq. (24):

$$p_i = \frac{fit_i}{\sum_{n=1}^{SN} fit_n} \tag{24}$$

Step 4 – Scout bees: here, those employed bees that cannot find a better solution after some pre-determined iterations become scout bees to enhance the efficiency of the ABC algorithm, and their obtained solutions are abandoned. By moving in random paths, the scout bees start searching for new food sources according to Eq. (21); accordingly, the food sources that are initially weak, or become so after utilization, are excluded. Studies have shown that execution of Step 4 will highly increase the likelihood of finding a general optimum solution. The process of optimization will be continued until converged. Two convergence criteria are in fact active in the process. First, if the changes on the optimum objective values are so negligible in 10 consecutive iterations. If so, we make sure the recorded optimum solution does not violate constraints, as a result of which completion of the process will be informed. The second option, being in fact a termination criterion, is that of the maximum iterations allowed. The process will therefore halt if either of the two criteria is reached.The step-by-step flowchart of the ABC optimization algorithm is shown in Fig. 2.

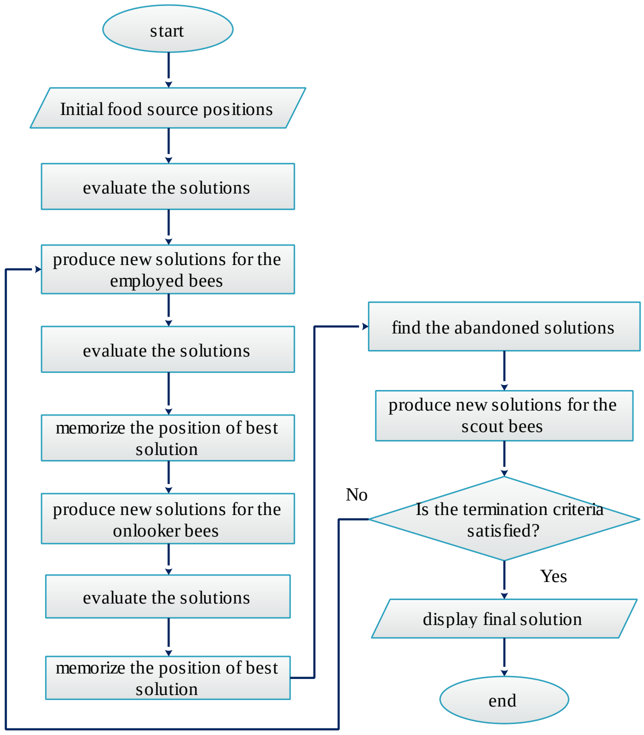


Fig. 2 Step-by-step flowchart of the ABC optimization algorithm

5. RBF-ABC optimization

In this method, as for the purpose of utilizing the RBF neural network, for each example separately, a database was required to train the network. Thus:

1. A number of 300 Simulations were first generated randomly, using uniform distribution approach in the given parameters space for all design variables (size, shape or topology).
2. The MSTOWER software was then involved to analyze the sampling points.
3. 70% of the evaluated dataset were then employed to train the RBF network, a target of which reached when the MSE error is within the allowed set value of 0.001% error.
4. The trained network was then tested on 30% of the remaining of the sampling points. The outcome is set as satisfactory if the maximum discrepancy of the network-based results do not exceed a second predetermined desired fallout of 0.1%, in which case the RBF trained network substitute the MSTOWER software for the analysis. If not so, more sampling points would be added to the training dataset, a sequence of which is repeated until a satisfactory training and testing processes are encountered.

The vector of the design variables of the optimization problem is the input to the network, and the transmission tower weight and the total constraint violations are its objective outputs. Accordingly, by selecting proper RBF network parameters, two RBF neural networks have been trained to replace the relevant analyzer in the transmission towers' optimization process; they play important roles in reducing the volume of computations Since the more is the number of design variables, the more complex will the RBF network training become, effort has been made to avoid using a large number of design variables as far as possible.

To evaluate the learning rate and performance of the trained networks, the values of the mean square error (MSE), the mean absolute error (MAE) between the actual outputs and network, and the correlation coefficient (R^2) have been calculated using Eqs. (25)-(27); the training program of the RBF neural network has also been coded in the MATLAB Software.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - t_i)^2 \tag{25}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\frac{|y_i - t_i|}{t_i} \tag{26}$$

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{N}(y_i - t_i)^2}{\sum_{i=1}^{N} t_i^2}\right) \tag{27}$$

where y_i and t_i are the network and actual outputs, respectively, and N is the number of pairs of training/testing.

6. MSTOWER-ABC optimization

To compare the results obtained from the RBF-ABC method, optimization has also been done using the MSTOWER-ABC method. This method is similar to the previous one with the only difference that the MSTOWER Software is used as the analyzer in the optimization process. MSTOWER is a specialized software package for the modeling of power transmission towers. It is advantageous

Table 1 Parameters of the ABC algorithm in the optimization process for both methods

ABC Parameters	CIGRÉ Tower	132 GMS kv Tower
SN	30	30
Maxcycle	100	150
Limit	30	30
ndim	(0.1*nvar)	(0.4*nvar)

where SN = total number of bees, Maxcycle = max number of iterations, Limit = max number of unimproved iterations, and ndim = number of dimensions on which movements occur.

because it not only has different codes related to all power transmission towers, but it can also model a tower easily either graphically or using standard panels available in the software; this paper does the modeling using the second method. The initial tower design is first modeled in the MSTOWER, then the ABC algorithm parameters are initialized, and finally, the design variables are randomly selected within the permissible range based on the desired optimization method (size, shape and size, shape, size, and topology). Next, the optimization process continues by linking the MATLAB with MSTOWER until the convergence criteria are met. The calculation time is quite lengthy in this method and may take several days. Fig. 3 shows the general flowchart of both optimization methods.

7. Numerical examples

To illustrate the performance of the method presented in this paper, the CIGRÉ Tower (CIGRÉ 2009) and the 132 GMS kV transmission tower were considered as two numerical examples and will now be explained in detail. The design requirements (ASCE10-97 (2000)) and load case (IEC 60652 (2002)) are similar for both examples and the parameters of the ABC algorithm in the optimization process for both methods are presented in Table 1.

7.1 CIGRÉ Tower

To validate the proposed method, this paper has used the CIGRÉ tower (CIGRÉ 2009) (Fig. 4) as a benchmark example for the modeling of which all the needed structural data are available. Souza *et al*. (2014) optimized its size and shape as well as its topology (Souza *et al*. 2016) Its structure is made of the ASTM A572 g 50 steel with 12 mm diameter bolts on which 8 different load cases (Table 2) have been applied. The original model has been designed and analyzed by the MSTOWER Software and the data needed to train and test the neural network (70% for training and 30% for tests) for optimization by the RBF-ABC method have been obtained through multiple analyses. After training the relevant neural networks, the tower was optimized once by the RBF-ABC method and once by the MSTOWER-ABC method.

7.1.1 Size optimization

To optimize the size of the CIGRÉ Tower (CIGRÉ 2009), it was first grouped into different groups (Fig. 4) and 6 design variables were then defined accordingly; X = {A_1, A_2... A_6} is the vector of the design variables (inputs to the neural network) where A is the number of the angle profiles selected from a discrete catalog list that includes 43 European angle profiles(Table 3). Before starting the RBF-ABC optimization process, 300 analyses were done by the MSTOWER Software to train the neural network and the tower weight and the total constraint violations of the

Table 2 Loading applied to the CIGRÉ Tower

Case	Position	Fx (N)	Fy (N)	Fz (N)
1	A	0.00	0.00	0.00
	B	0.00	0.00	-49033
2	A	0.00	0.00	-49033
	B	0.00	0.00	-49033
3	A	0.00	0.00	0.00
	B	49033	0.00	0.00
4	A	49033	0.00	0.00
	B	49033	0.00	0.00
5	A	0.00	0.00	0.00
	B	0.00	49033	0.00
6	A	0.00	49033	0.00
	B	0.00	49033	0.00
7	A	0.00	0.00	0.00
	B	49033	49033	-49033
8	A	49033	49033	-49033
	B	49033	49033	-49033

Table 3 Available profiles for the size optimization of the CIGRÉ Tower

L30X30X3	L40X40X5	L60X60X5	L60X60X8
L35X35X3	L50X50X4	L55X55X6	L80X80X6
L30X30X4	L55X55X4	L65X65X5	L70X70X7
L40X40X3	L45X45X5	L70X70X5	L65X65X8
L45X45X3	L40X40X6	L60X60X6	L75X75X7
L35X35X4	L60X60X4	L75X75X5	L90X90X6
L30X30X5	L50X50X5	L50X50X8	L70X70X8
L50X50X3	L45X45X6	L65X65X6	L75X75X8
L40X40X4	L65X65X4	L70X70X6	L100X100X6
L35X35X5	L55X55X5	L55X55X8	L90X90X7
L45X45X4	L50X50X6	L75X75X6	

Table 4 Neural network Statistical Criteria for the size optimization of the CIGRÉ Tower

Statistical Criteria	Total Weight		Total Constraint Violation	
	Train Data	Test Data	Train Data	Test Data
MSE	6.4×10^{-6}	6.7×10^{-6}	7.9×10^{-14}	2.0×10^{-14}
MAE	2×10^{-3}	2×10^{-3}	1.2×10^{-7}	7.8×10^{-8}
R^2	0.997	0.997	0.999	0.999

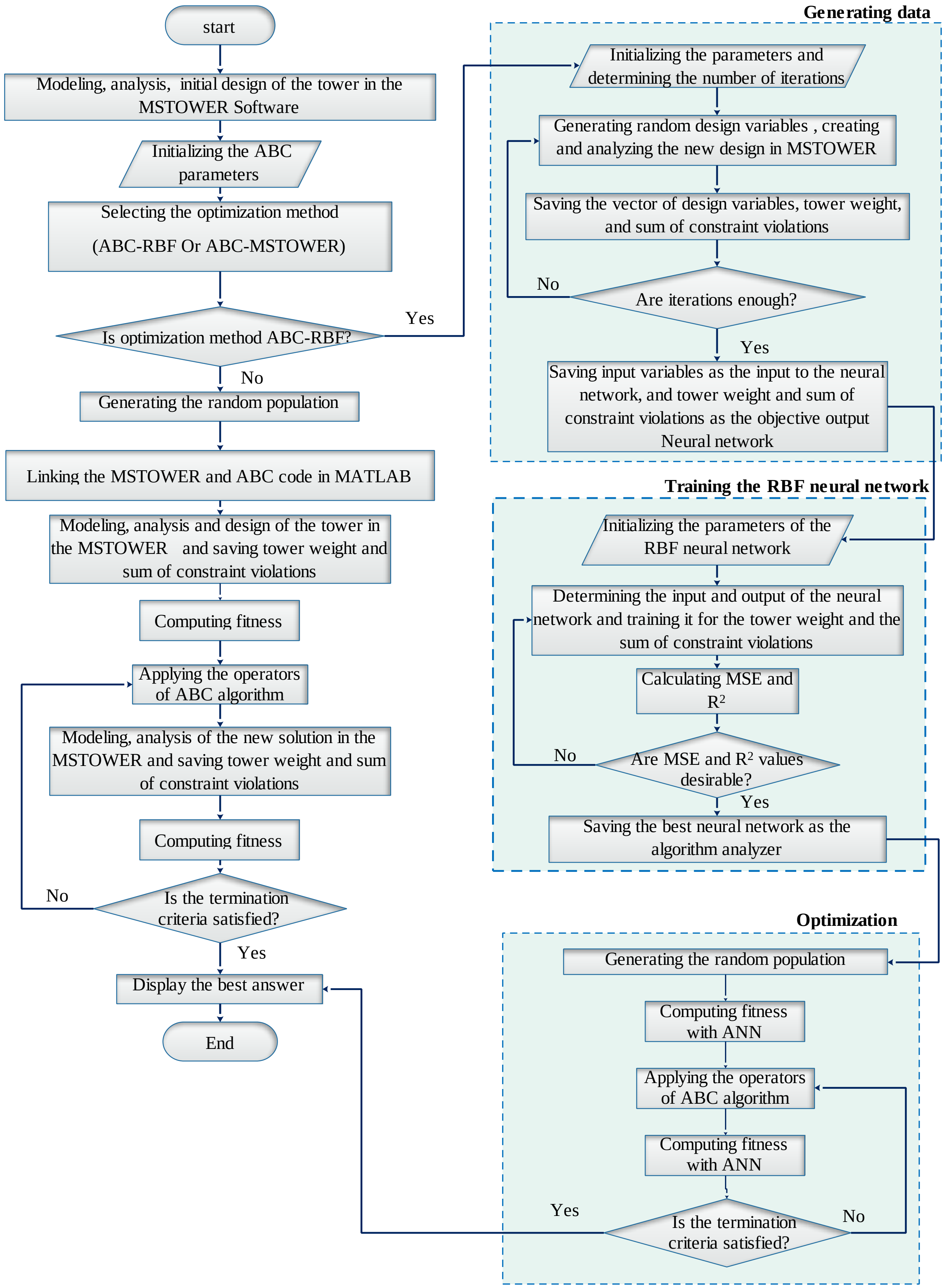
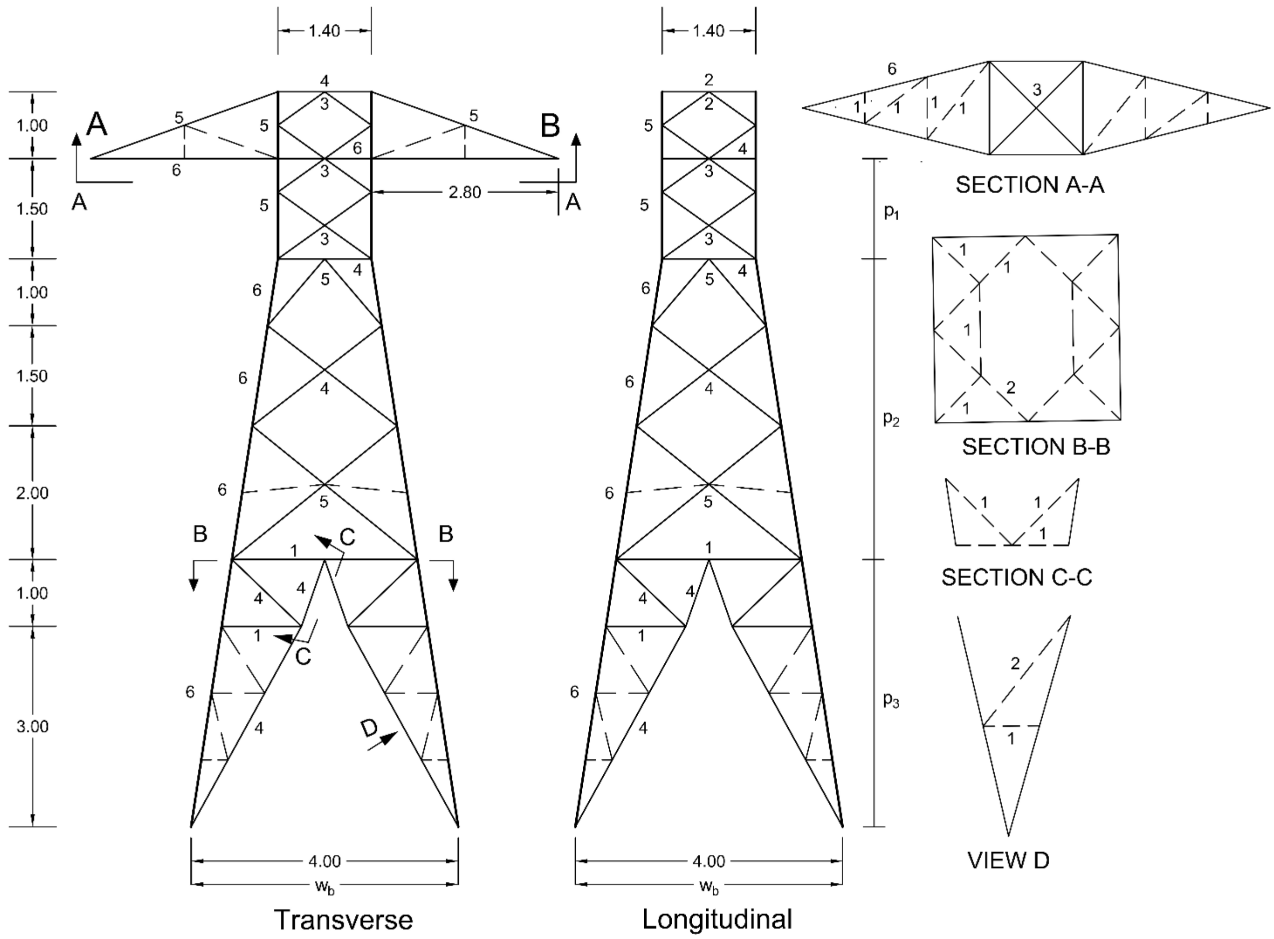


Fig. 3 General flowchart of both MSTOWER-ABC and RBF-ABC optimization methods



Note: (a) The numbers represent the grouping of tower elements (b) P_m, m^{th} design variable of topology optimization (c) Dimensions in meters

Fig. 4 Initial modeling of the the CIGRÉ tower

members (objective outputs of the neural network) were stored. The best trained network was then stored as the analyzer in the optimization process.

Table 4 shows the errors in the training/test data and the related R^2 (as shown, the trained neural network has good performance), and Table 5 shows the tower size optimization results found by the RBF-ABC and MSTOWER-ABC methods and their analyses time.

According to Table 5, the optimized weights are 1203.11 and 1198.2 kg and optimization times are 63.45 and 1438.55 minutes with the RBF-ABC and MSTOWER-ABC methods, respectively. Since the optimized weights are close, it means that the neural network performs well because a time comparison of the two methods shows that it has reduced the analysis time effectively. Souza *et al.* (2016) optimized the CIGRÉ Tower (CIGRÉ 2009) differently by ignoring the redundant members in calculating the weight. However, the present paper has considered weight of the redundant members into account to compare the optimized tower weight (1201.6 kg) with that in Souza *et al.* (2016). The comparison showed that the weight found by the MSTOWER-ABC method was 0.29 % less (than those in Souza *et al.* (2016)). Fig. 5 shows the convergence diagram of the ABC optimization algorithm.

7.1.2 Optimization of the size and shape

To optimize the size and shape of the CIGRÉ Tower (CIGRÉ 2009) with the RBF-ABC method, two new networks were trained (and used as analyzers in the optimization process) for the tower weight and total constraint violations of the members using the stored data through 300 analyses performed by the MSTOWER. The MSE, MAE, and R^2 values of the training/test data in Table 6 show that the trained neural network has had a good performance. The tower base width has also been used (in both x and y directions alike) as design variable for the size and shape optimization. A change in the base width, according to the tower body slope, will also change the widths of the panels in the sloping body. Since the base width design variable has been selected discretely every 10 cm in the range 3-5 m, the vector of the design variables has been defined as $X=\{A_1,A_2,\ldots,A_6,W_b\}$ where W_b is the width of the tower base. Fig. 6 and Table 7 show, respectively, the convergence diagram of the optimization algorithm and the optimization results obtained by both methods presented optimized in this paper. Table 7 shows that with the RBF-ABC method, the optimized weight and the total optimization process time are 1148.273 kg and 64.328 minutes and with the MSTOWER-ABC method, they are

Table 5 Comparison of the Size optimization results of RBF-ABC and MSTOWER-ABC for the CIGRÉ Tower

Design Variables	Methods	
	RBF-ABC	MSTOWER-ABC
A_1	L 40×40×3	L 40×40×3
A_2	L 45×45×3	L 40×40×3
A_3	L 45×45×4	L 45×45×4
A_4	L 55×55×4	L 55×55×4
A_5	L 60×60×4	L 60×60×4
A_6	L 75×75×7	L 75×75×7
Weight (kg)	**1203.113**	**1198.200**
Data generation time(min.)	63.125	-
Training time (min.)	0.166	-
Optimization time(min.)	**0.160**	**1438.552**

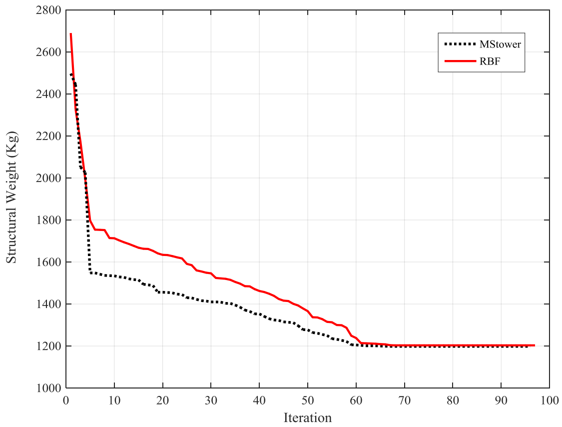


Fig. 5 Convergence diagram of the size optimization of the CIGRÉ Tower

1133.7 kg and 1751.01 minutes. As mentioned before, the weight optimized in Souza *et al.* (2016) with the Backtracking Search Algorithm (BSA) method was 1185.12 kg which means that the weights obtained with the MSTOWER-ABC and RBF-ABC were respectively 4.3 and 3.1% less than those in Souza *et al.* (2016). In shape optimization, a decrease in the base width of the transmission tower will narrow the tower shape and, hence, decrease the free lengths of the members. This will make the tower exhibit a better buckling-resistance behavior and cause members to get thinner.

7.1.3 Optimization of the size, shape and topology

Like previous RBF-ABC optimizations, a new analyzer was created for the tower weight and the total constraint violations of the members using the neural network training and the data stored from 300 MSTOWER Software analyses. The MSE, MAE, and R^2 of the training/test data in Table 8 show that the trained neural network functions well. Panels' shapes too have been considered as design variables to simultaneously optimize the tower size, shape, and topology; in some parts of the tower, shapes of the panels (selected from a standard list available in MSTOWER) change until a panel is selected that can yield the optimum solution.

Table 6 Neural network Statistical Criteria for the size and shape optimization of the CIGRÉ Tower

Statistical Criteria	Total Weight		Total Constraint Violation	
	Train Data	Test Data	Train Data	Test Data
MSE	9.2×10^{-6}	1.5×10^{-5}	2.7×10^{-14}	3.6×10^{-14}
MAE	2×10^{-3}	2×10^{-3}	9×10^{-8}	9.2×10^{-8}
R^2	0.996	0.990	0.999	0.999

Table 7 Comparison of the Size and shape optimization results of RBF-ABC and MSTOWER-ABC for the CIGRÉ Tower

Design Variables	Methods	
	RBF-ABC	MSTOWER-ABC
A_1	L 40×40×3	L 40×40×3
A_2	L 35×35×3	L 40×40×3
A_3	L 40×40×5	L 45×45×4
A_4	L 55×55×4	L 50×50×4
A_5	L 60×60×4	L 60×60×4
A_6	L 80×80×6	L 75×75×7
W_b (m)	3.500	3.500
Weight (kg)	**1148.273**	**1133.700**
Data generation time(min.)	63.540	-
Training time (min.)	0.267	-
Optimization time(min.)	0.521	1758.013
Overall Time(min.)	**64.328**	**1758.013**

Fig. 4 shows the three design variables selected for the topology optimization. This paper has prepared and used a list of 7 different panel shapes in the x and y directions: As shown in Appendix (a), The number of panel options for P1, P2 and P3 are 3, 2 and 2, respectively. The vector of the design variables for the simultaneous optimization of the size, shape, and topology has been defined as $X=\{A_1,A_2,\ldots,A_6,P_1,P_2,P_3,W_b\}$ where A is the number of the angle profiles in the existing catalog list, P is the number of panel shapes in the existing list for the parts the shapes of which vary, and W_b is the tower base width.

To evaluate the RBF-ABC method performance, optimization has also been done with the MSTOWER-ABC method and results of the comparison, the convergence diagram of the ABC algorithm, and the final result of the optimized tower have been shown in Table 9, Figs. 7 and 8, respectively; the latter also shows the panels that have changed during the topology optimization process. Topology affects the structure stiffness and panels' variations and, hence, changes in the number of the tower forming members can increase the structure stiffness and, hence, reduce the tower weight.

According to Table 9, the optimized weights are 1107.40 and 1079.97 kg and optimization times are 71.945 and 1826.017 minutes with RBF-ABC and MSTOWER-ABC methods, respectively. Since the optimized weights are close, it means that the neural network performs well because a time comparison of the two methods shows that it has reduced the analysis time effectively.

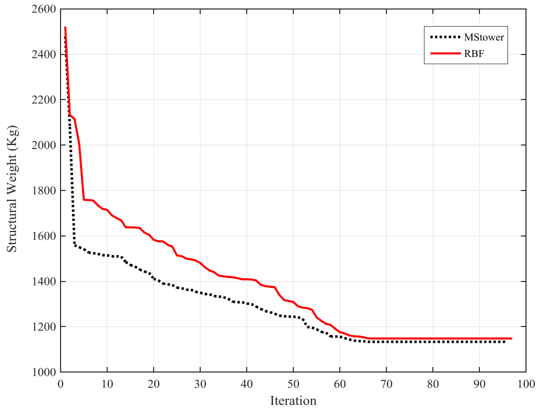


Fig. 6 Convergence diagram of the optimization of the size and shape of the CIGRÉ Tower

Table 8 Neural network Statistical Criteria for the optimization of the size, shape, and topology of the CIGRÉ Tower

Statistical Criteria	Total Weight		Total Constraint Violation	
	Train Data	Test Data	Train Data	Test Data
MSE	3.4×10^{-4}	8×10^{-3}	6.2×10^{-6}	2.1×10^{-3}
MAE	0.012	0.033	0.001	0.011
R^2	0.994	0.930	0.999	0.986

Table 9 Comparison of the size, shape and topology optimization results of RBF-ABC and MSTOWER-ABC for the CIGRÉ Tower

Design Variables	Methods	
	RBF-ABC	MSTOWER-ABC
A_1	L 40×40×3	L 40×40×3
A_2	L 35×35×3	L 35×35×3
A_3	L 45×45×4	L 50×50×3
A_4	L 50×50×4	L 50×50×4
A_5	L 60×60×4	L 60×60×4
A_6	L 80×80×6	L 70×70×7
W_b (m)	3.500	3.500
Weight (kg)	**1107.400**	**1079.970**
Data generation time(min.)	70.730	-
Training time (min.)	0.267	-
Optimization time(min.)	0.948	1826.017
Overall Time(min.)	**71.945**	**1826.017**

Since the best result obtained for the simultaneous optimization of the size, shape, and topology of the CIGRÉ Tower in Souza *et al.*'s paper (2016) has been 1143.52 kg, the weights obtained with the MSTOWER-ABC and RBF-ABC methods are 5.6 and 3.2% less than those found in Souza *et al.* (2016).

Bar graphs in Figs. 9 and 10 compare, respectively, the optimized weights and optimization times for the CIGRÉ Tower with the RBF-ABC, MSTOWER-ABC and BSA methods.

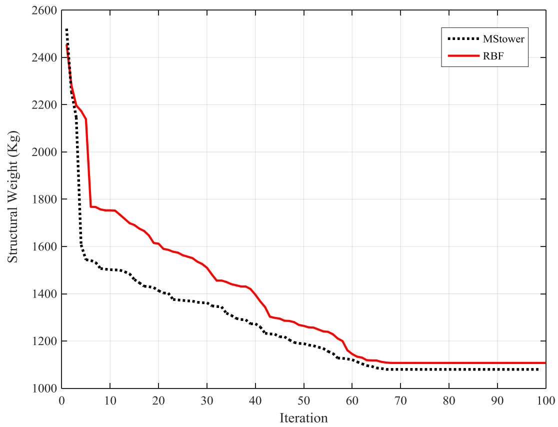


Fig. 7 Convergence diagram of the optimization of the size, shape and topology of the CIGRÉ Tower

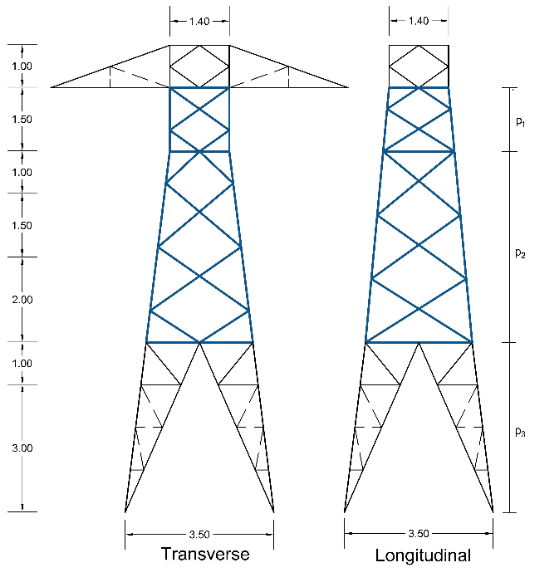


Fig. 8 Final result of the size, shape and topology optimization of CIGRÉ Tower (all units are in meters)

7.2 The 132 GMS kV transmission tower

As a second example, a real, 45 m-high, 2625-member, 14273.81 kg, 132 GMS kV tower has been studied in this paper (Fig. 11). The steel is st52, the bolt diameter is 17.5 mm, and the applied load is as in Table 10 based on which 110 load cases have been defined for this tower. It was first modeled and initially designed in the MSTOWER Software and then two neural networks were trained for the tower weight and total constraint violations of the members using the information from several different analyses. It is worth noting that two separate neural networks (considered as analyzers in the optimization process) were trained for each RBF-ABC optimization method (size, shape and size, and size, shape, and topology).

7.2.1 Optimization of size

The tower has been grouped according to Fig. 11 and a total of 17 design variables have been used to optimize its size. The variables are related to the members' cross-sectional areas and are selected from a discrete catalog list

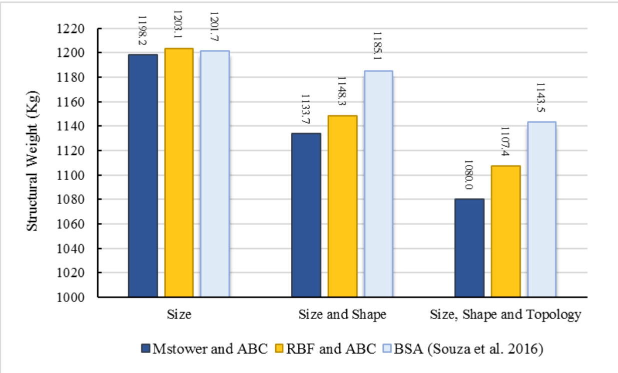


Fig. 9 Weight comparison of the CIGRÉ Tower optimized with three different methods (size, size and shape, size, shape, and topology)

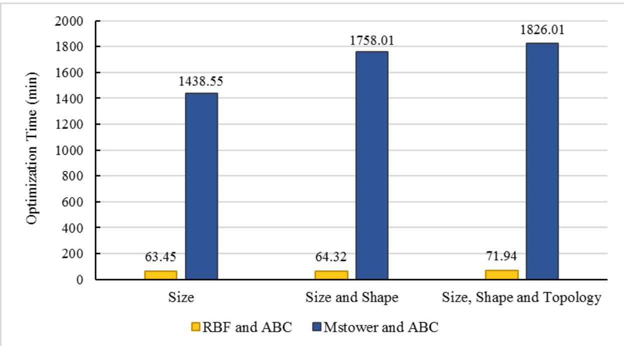


Fig. 10 Comparison of the time required for the optimization of the CIGRÉ Tower with three different methods (size, size and shape, size, shape, and topology)

of 58 European angle profiles (Table 11). The vector of the design variables has been defined as $X=\{A_1,A_2,\dots,A_{17}\}$ and the analyzer used in the RBF-ABC optimization process has been trained using the weight and constraint violations found, after 500 analyses, from the MSTOWER.

To evaluate the neural network, the MSE, MAE, and R^2 of the training and test data are shown in Table 12 based on which the trained neural network functions well. The convergence diagram and results found from the optimization with the RBF-ABC and MSTOWER-ABC methods are given in Fig. 12 and Table 13, respectively.

As shown in Table 13, the optimized weights are 11029.203 and 10922.35 kg and optimization times are 279.36 and 4642.69 minutes with the RBF-ABC and MSTOWER-ABC methods, respectively.

Since the optimized weights are close, it means that the neural network performs well because a time comparison of the two methods shows that it has reduced the analysis time effectively.

7.2.2 Optimization of size and shape

To optimize the size and shape of the 132 GMS kV transmission tower by the RBF-ABC method, the tower base width has been considered as the design variable and two new networks have been trained (and used as analyzers in the optimization process) for the tower weight and the members' constraint violations using the data found from 500 MSTOWER analyses.

Table 10 Loading applied to the 132 kV transmission tower

No.	Load Case	Conductor Loads (kg)			Shield Peak Loads(kg)		
		Trans	Vertical	Long	Trans	Vertical	Long
1	High wind	1081	633	-	540	308	-
2	Heavy ice	204	1553	-	153	947	-
3	Wind & ice	1549	1322	-	1095	699	-
4	Broken wire in heavy ice	102	958	2338	77	568	2926
5	Unbalanced in wind & ice	624	801	364	394	410	866

Table 11 Available profiles for the size optimization of the 132 kV transmission tower

L30X30X3	L50X50X4	L65X65X5	L90X90X12
L30X30X4	L50X50X5	L70X70X5	L100X100X6
L30X30X5	L50X50X6	L70X70X6	L100X100X8
L35X35X3	L50X50X8	L70X70X7	L100X100X10
L35X35X4	L55X55X4	L70X70X8	L100X100X12
L35X35X5	L55X55X5	L75X75X5	L110X110X8
L40X40X3	L55X55X6	L75X75X6	L110X110X10
L40X40X4	L55X55X8	L75X75X7	L110X110X12
L40X40X5	L60X60X4	L75X75X8	L120X120X8
L40X40X6	L60X60X5	L80X80X6	L120X120X10
L45X45X3	L60X60X6	L80X80X8	L120X120X12
L45X45X4	L60X60X8	L90X90X6	L130X130X10
L45X45X5	L65X65X4	L90X90X7	L130X130X12
L45X45X6	L65X65X6	L90X90X8	
L50X50X3	L65X65X8	L90X90X10	

Table 12 Neural network Statistical Criteria for size optimization of the 132 kV transmission tower

Statistical Criteria	Total Weight		Total Constraint Violation	
	Train Data	Test Data	Train Data	Test Data
MSE	4.1×10^{-5}	1×10^{-4}	2.3×10^{-4}	4.3×10^{-4}
MAE	0.004	0.004	0.003	0.005
R^2	0.999	0.997	0.999	0.974

To evaluate the neural network, the MSE, MAE, and R^2 of the training and test data are shown in Table 14 based on which the trained neural network functions well.

The base width is the same in both the x and Y directions and a change in it will also change the panels' widths in the tower sloping body.

Since the base width design variable has been selected discretely every 10 cm in the range 9-11 m, the vector of the design variables has been defined as $X=\{A_1,A_2,\dots,A_{17},W_b\}$where W_b is the width of the tower base selected randomly in a known interval. Table 15 shows the optimization results found from both methods.

According to Table 15, the optimized weights are 10813.63 and 10736.33 kg and optimization times are 321.45 and 4652.85 minutes with the RBF-ABC and MSTOWER-ABC methods, respectively. Since the

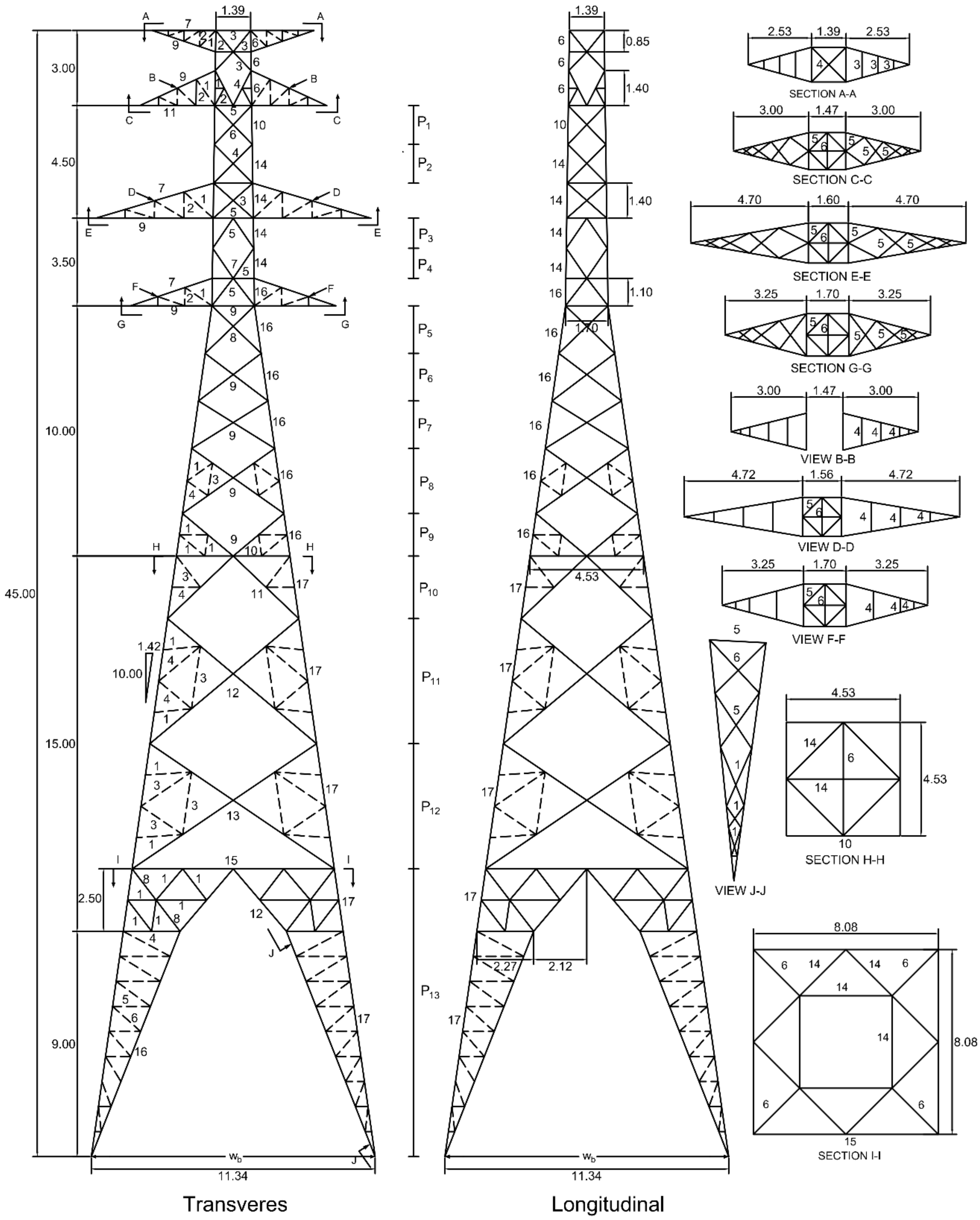


Fig. 11 Initial modeling of the 132 kV transmission tower (all units are in meters)

optimized weights are close, it means that the neural network performs well because a time comparison of the two methods shows that it has reduced the analysis time effectively. The convergence diagram of the optimization algorithm is shown in Fig. 13. In shape optimization, a decrease in the base width of the transmission tower will narrow the tower shape and, hence, decrease the free lengths of the members. This will make the tower exhibit a better buckling-resistance behavior and cause members to get thinner.

7.2.3 Optimization of the size, shape and topology

Like previous optimizations, a new analyzer has been developed for the RBF-ABC optimization through 500 analyses of the data stored in the MSTOWER. The MSE, MAE and R^2 of the training/test data presented in Table 16 show that the neural network is well-trained. For the simultaneous optimization of the size, shape, and topology, panels' shapes have also been considered as design variables; as shown in Fig. 11, they go on varying in some portions of the tower until a panel is selected that yields the optimum solution. These panels are selected from a standard list available in the MSTOWER Software.

Table 13 Comparison of the Size optimization results of RBF-ABC and MSTOWER-ABC for the 132kV transmission tower

Design Variables	Methods	
	RBF-ABC	MSTOWER-ABC
A_1	L 50×50×4	L 50×50×3
A_2	L 50×50×4	L 50×50×4
A_3	L 55×55×4	L 55×55×4
A_4	L 55×55×4	L 55×55×4
A_5	L 55×55×4	L 55×55×4
A_6	L 60×60×4	L 60×60×4
A_7	L 60×60×4	L 60×60×4
A_8	L 60×60×4	L 60×60×4
A_9	L 70×70×5	L 65×65×5
A_{10}	L 70×70×5	L 70×70×5
A_{11}	L 70×70×5	L 70×70×5
A_{12}	L 100×100×6	L 100×100×6
A_{13}	L 120×120×8	L 120×120×8
A_{14}	L 80×80×6	L 80×80×6
A_{15}	L 100×100×6	L 100×100×6
A_{16}	L 110×110×8	L 110×110×10
A_{17}	L 110×110×10	L 110×110×8
Weight (kg)	**11029.203**	**10922.350**
Data generation time(min.)	277.750	-
Training time (min.)	0.667	-
Optimization time(min.)	0.946	4642.699
Overall Time(min.)	**279.363**	**4642.699**

Table 14 Neural network Statistical Criteria for the optimization of the size and shape of the 132 kV transmission tower

Statistical Criteria	Total Weight		Total Constraint Violation	
	Train Data	Test Data	Train Data	Test Data
MSE	2.5×10^{-5}	5.8×10^{-4}	1×10^{-4}	3.7×10^{-3}
MAE	0.003	0.013	0.006	0.029
R^2	0.999	0.996	0.998	0.971

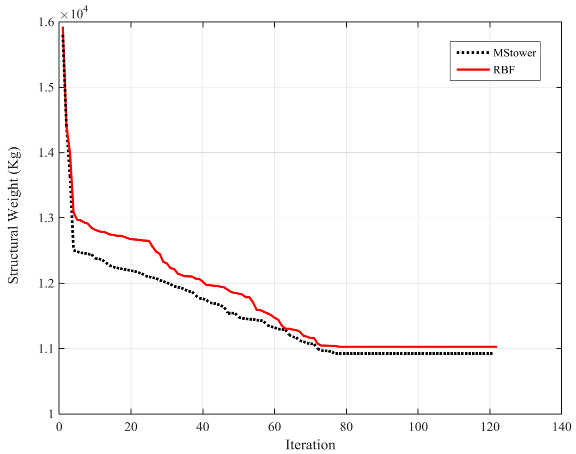


Fig. 12 Convergence diagram of the optimization of the size of the 132 kV transmission tower

Table 15 Comparison of the Size and shape optimization results of RBF-ABC and MSTOWER-ABC for the 132 kV transmission tower

Design Variables	Methods	
	RBF-ABC	MSTOWER-ABC
A_1	L 50×50×4	L 50×50×4
A_2	L 50×50×4	L 50×50×4
A_3	L 55×55×4	L 55×55×4
A_4	L 55×55×4	L 55×55×4
A_5	L 60×60×4	L 60×60×4
A_6	L 65×65×4	L 65×65×4
A_7	L 60×60×4	L 60×60×4
A_8	L 70×70×5	L 70×70×5
A_9	L 70×70×5	L 70×70×5
A_{10}	L 70×70×5	L 70×70×5
A_{11}	L 70×70×5	L 70×70×5
A_{12}	L 100×100×6	L 100×100×6
A_{13}	L 120×120×8	L 120×120×8
A_{14}	L 90×90×6	L 80×80×6
A_{15}	L 90×90×6	L 80×80×6
A_{16}	L 110×110×8	L 110×110×8
A_{17}	L 110×110×10	L 110×110×10
W_b (m)	10.000	10.000
Weight (kg)	**10813.626**	**10736.330**
Data generation time(min.)	319.833	-
Training time (min.)	0.733	-
Optimization time(min.)	0.882	4652.850
Overall Time(min.)	**321.448**	**4652.850**

In this paper number of panels to select from for topology optimization of 132 KV tower is 33 (As shown in Appendix (a)) and the total design variable for size, shape and topology optimization is 31.The vector of design variables is defined as $X=\{A_1,A_2,\ldots,A_{17},P_1,P_2,\ldots,P_{13},W_b\}$ A is the number of the angle profiles selected from a discrete catalog list, P is that of the panels the shapes of which vary, and W_b is the width of the tower base selected randomly in a known interval.

Results and analysis time of RBF-ABC and MSTOWER-ABC optimization methods are shown in Table 17. According to Table 17, the optimized weights are 10671.79 and 10482.35 kg and optimization times are 367.89 and 4665.04 minutes with the RBF-ABC and MSTOWER-ABC methods, respectively. Since the optimized weights are close, it means that the neural network performs well because a time comparison of the two methods shows that it has reduced the analysis time effectively. Figs. 14 and 15, and Table 18 show, respectively, the convergence diagram of the ABC algorithm, final result of the optimized tower (and panels changed in the optimization process), and the best results obtained from the three different optimization methods (and percent reduction of the structure weight compared to the initial design).

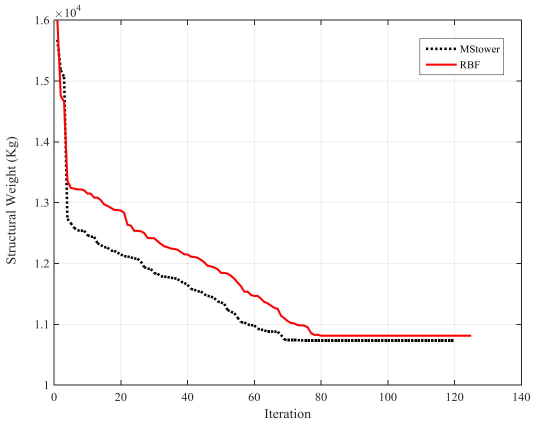


Fig. 13 Convergence diagram of the optimization of the size and shape of the 132 kV transmission tower

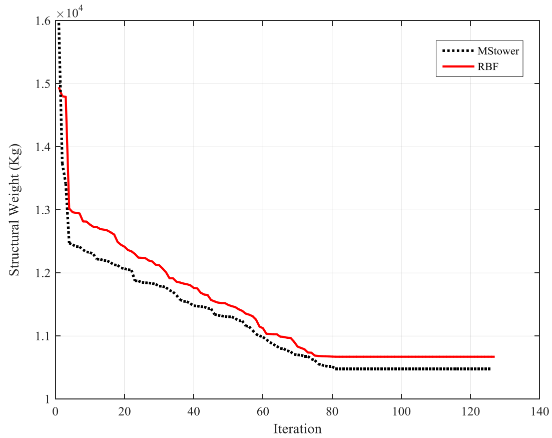


Fig. 14 Convergence diagram of the optimization of the size, shape, and topology of the 132 kV transmission tower

Table 16 Neural network Statistical Criteria for the optimization of the size, shape and topology of the 132 kV transmission tower

Statistical Criteria	Total Weight		Total Constraint Violation	
	Train Data	Test Data	Train Data	Test Data
MSE	1.2×10^{-4}	2.8×10^{-4}	4×10^{-5}	3.4×10^{-4}
MAE	0.005	0.007	0.001	0.002
R^2	0.999	0.998	0.999	0.995

Table 17 Comparison of the size, shape and topology optimization results of RBF-ABC and MSTOWER-ABC for the 132 kV transmission tower

Design Variables	Methods	
	RBF-ABC	MSTOWER-ABC
A_1	L 50×50×3	L 50×50×3
A_2	L 40×40×3	L 40×40×3
A_3	L 55×55×4	L 55×55×4
A_4	L 60×60×4	L 60×60×4
A_5	L 60×60×4	L 60×60×4
A_6	L 65×65×4	L 65×65×4
A_7	L 60×60×4	L 65×65×5
A_8	L 60×60×8	L 70×70×5
A_9	L 60×60×4	L 60×60×4
A_{10}	L 70×70×5	L 70×70×5
A_{11}	L 70×70×7	L 70×70×7
A_{12}	L 80×80×6	L 75×75×6
A_{13}	L 110×110×8	L 110×110×8
A_{14}	L 80×80×6	L 80×80×6
A_{15}	L 100×100×6	L 100×100×6
A_{16}	L 120×120×8	L 120×120×8
A_{17}	L 120×120×10	L 120×120×10
W_b (m)	10.000	10.000
Weight (kg)	**10671.787**	**10482.350**
Data generation time(min.)	336.667	-
Training time (min.)	0.815	-
Optimization time(min.)	0.410	4665.044
Overall Time(min.)	**367.892**	**4665.044**

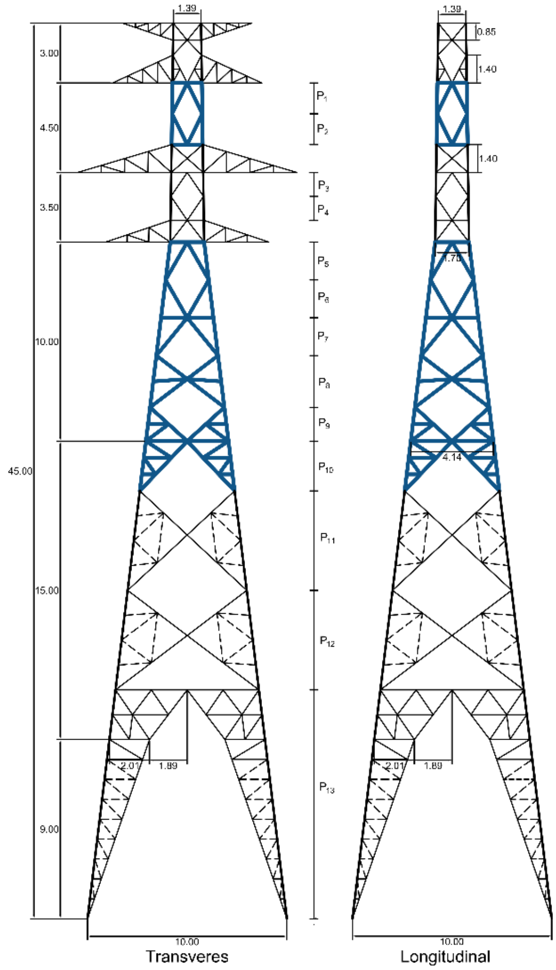


Fig. 15 Final result of the size, shape and topology optimization of the 132 kV transmission tower (all units are in meters).

As shown, the simultaneous optimization of the size, shape, and topology has highly reduced the structure weight. General comparisons of the RBF-ABC and MSTOWER-ABC methods for the optimized weight and optimization process time (of the 132 kV transmission tower) are shown in the bar graphs of Figs. 16 and 17, respectively.

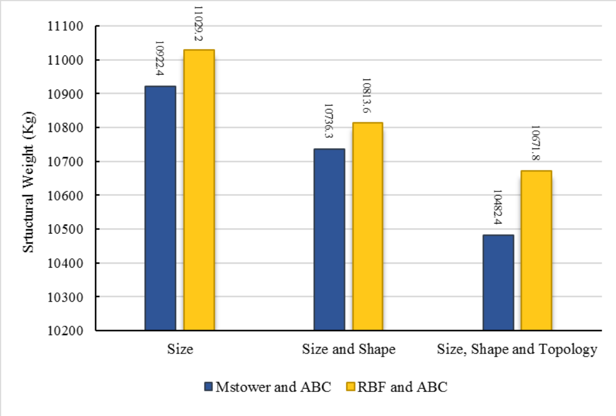


Fig. 16 Weight comparison of the 132 kV transmission tower optimized with three different methods (size, size and shape, size, shape, and topology)

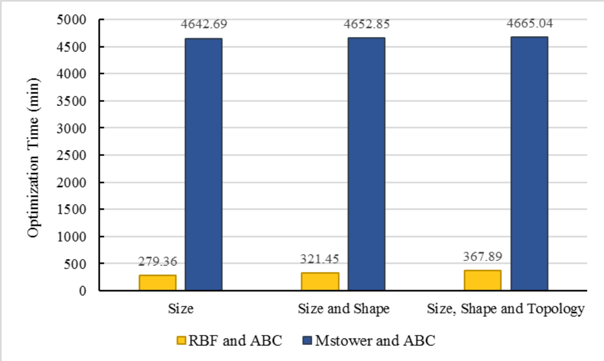


Fig. 17 Comparison of the time required for the optimization of the 132 kV transmission tower with three different methods (size, size and shape, size, shape, and topology)

Table 18 Final result of the size, shape, and topology optimization of the 132 kV transmission tower

Optimization	Methods			
	RBF & ABC		MStower & ABC	
	Weight (kg)	Reduction	Weight (kg)	Reduction
Size	11029.2	22.7 %	10922.3	23.4%
Size and Shape	10813.6	24.2 %	10736.3	24.7 %
Size, Shape and Topology	10671.7	25.2 %	10482.3	25.5 %

Topology affects the structure stiffness and panels' deformations and, hence, the change in the number of the tower forming members can increase the structure stiffness and, hence, reduce the tower weight.

8. Conclusions

Since transmission towers are among the main infrastructures of the power industry in every country, their optimization can considerably reduce the relevant costs of this industry. This paper is aimed to address the simultaneous optimization of the size, shape, and topology of these towers through a practical method. To this end, first, a benchmark problem presented by CIGRÉ was reviewed and, then, a real case, a 132 kV suspension tower, was studied. Both towers were modeled, analyzed, and initially designed by the MSTOWER Software considering the design requirements of the ASCE10-97 Code (2000), and optimized by the artificial bee colony (ABC) algorithm. Since optimization with metaheuristic methods is quite time consuming, use was made of their combinations with neural networks and the towers were optimized using the MSTOWER-ABC method. In shape optimization, a decrease in the base width of the transmission tower will narrow the tower shape and, hence, decrease the free lengths of the members. This will make the tower exhibit a better buckling-resistance behavior and cause members to get thinner.

Besides, topology will affect the structure stiffness and changes in the panels' shapes and, hence, the change in the number of the tower forming members can increase the structure stiffness and thereby reduce the tower weight. A comparison of the results of the three optimization methods (size, size/shape, and size/shape/topology) in both the RBF-ABC and MSTOWER-ABC methods shows that the simultaneous optimization of the size, shape, and topology of the towers plays a greater part in their weight loss. For the CIGRÉ Tower; however, a comparison of the results obtained in this paper with those of the BSA method showed that the proposed method could further minimize the structural weight by about 6% and the 132 kV tower was minimized in weight by up to 25% compared to the initial design. Closeness of the results based on RBF-ABC and MSTOWER-ABC techniques showed that optimization with the former method is quite promising and it can be applied to other types of transmission towers through more efforts and evaluation of other examples.

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