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Artificial neural network-assisted supercell thunderstorm algorithm for optimization of real-world engineering problems

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Abstract: This study presents an artificial neural network (ANN)-assisted modified supercell thunderstorm optimizer (MSTO) for solving complex industrial component optimization problems. Inspired by the natural phenomena of spiral motion, tornado formation, and jet streams within supercell thunderstorms, the STO algorithm is enhanced with ANN integration to improve exploration, exploitation, and convergence rates. The algorithm is validated across five constrained engineering problems: cantilever beam optimization, industrial grinding cost optimization, tubular column design, diaphragm spring weight minimization, and fin and tube heat exchanger (FTHE) cost optimization. These results confirm MSTO's superior performance over recent metaheuristics, highlighting its potential for high-precision, stable, and efficient solutions across structural, thermal, and mechanical design domains.

Keywords: design optimization; industrial components; automobile components; spring design; artificial neural networks

1 Introduction

Optimizing product design for cost efficiency and core system integration is critical to industrial processes following product development. In addition, aside from engineering businesses, supply chain management systems, renewable energy-related companies, and transportation departments of all nations regularly need optimization [1], [2]. For many years, researchers have used traditional optimization strategies. However, these classical methodologies were retrofitted because of their practical advantages over conventional optimization methods, nature-inspired algorithms, or metaheuristics. For example, better computational time, global optimization solution, appropriate exploration–exploitation balance, and superior convergence rate [3]–[75]. The most fundamental category of metaheuristic (MH) algorithms includes those inspired by nature, innate intelligence, physics, evolution, and trajectory. Additionally, the categorization is not limited to the specified class; academics are analysing and creating new and more efficient forms of these metaheuristic algorithms.

In addition to these recently produced MHs, their efficient variants have also been used to tackle the problems of exploration capabilities, convergence rate, computation time, and the local optima trap [8]. As a result, these successful MHs are created using various strategies, including hybridization, upgrading chaotic maps, Levy flight tactics, and opposition-based approaches. These techniques are most commonly found in the realm of modified versions of MH's algorithms, yet they are insufficient. Additionally, multi-objective algorithms are suggested and evaluated to optimize multiple fitness functions. The developed algorithms resolved numerous engineering optimization problems, including those involving automotive and machine design [13]–[19].

This paper examines and applies the supercell thunderstorm optimization (STO) method, a recently created mathematically based nature-inspired algorithm, to five distinct engineering issue categories. For example, vertical column struts, industrial robots, vehicle components, and structural issues. The findings were derived using statistical data and contrasted with other competing findings found in existing research. Furthermore, the article's innovation lies in its use of the most innovative technique to solve engineering optimization issues that the researchers have not yet reported in the literature [9].

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2 Modified supercell thunderstorm optimizer (MSTO)

The studied algorithm, thunderstorm optimizer, is inspired by the natural occurrence of storms in different seasons. These storms occur in different variations depending on the atmospheric conditions and pressures. For instance, tornado, cyclone, spiral motion, and jet stream formation. Accordingly, the mathematical structure of the optimizer initiates with the selection of the random solutions populations in the search space as given by Equation (1) [23].

$$X_i = \mathrm{lb} + r_1(\mathrm{ub} - \mathrm{lb}), i = 1, 2, \ldots, n \quad (1)$$

Accordingly, the spiral motion in storm formation is a natural phenomenon generally observed in very strong vortices in hurricanes and tornadoes. The same can be given by Equation (2) [23].

$$X_i\,(t+1) = \begin{cases} \alpha_1\,(X_{\mathrm{best}}\,(t) + \beta_1\,(X_{\mathrm{best}}\,(t) - X_i\,(t)) + \alpha_2 X_i\,(t), \text{if } \alpha_1 < t/t_{\max} \\ \alpha_1\,(X_{\mathrm{best}}\,(t) + \beta_2\,(X_{\mathrm{best}}\,(t) - \mathrm{MG_i}\,(t)) + \alpha_2 X_i\,(t), \text{if } \alpha_1 \geq t/t_{\max} \end{cases} \quad (2)$$

with $\mathrm{MG_i}$: Mean group location for the considered candidate solution, α_1 and α_2: Coefficients that control the variables to move them towards the optimum solution, $t_{\max}$: Maximum number of iterations, and t: current iteration.

In the different categories of supercell thunderstorms, one of the strongest and most destructive patterns is tornadoes. As it is one of the most intense in nature, it creates disasters in a particular area. This tornado formation helps the optimizer to realize the local optimum solution, and the position can be altered according to the best solution. For instance, the mathematical formulation can be given by Equation (3) [23].

$$X_i\,(t{+}1) = \begin{cases} X_i\,(t) + \left\{\mathrm{rand}\,(0{,}1) \times \exp\left(-G_1 \times \dfrac{t}{t_{\max}}\right)\right] (X_{r3}\,(t) - X_{r4}\,(t)) \\ X_i\,(t) + [\mathrm{TF}\,(1 - \mathrm{rand}\,(0{,}1)) + \mathrm{rand}\,(0{,}1)]\,(X_{r3}\,(t) - X_{r4}\,(t)) \end{cases} \quad (3)$$

Furthermore, the jet stream targets the optimal point, and other points converge towards this point. The same can be given by Equation (4) [23].

The algorithm's computational complexity can be given by Equation (5).

$$O\,(\text{Supercell thunderstorm optimizer}) = O\,(2\mathrm{Tnd} + \mathrm{Tn} + n) \quad (5)$$

The developed algorithm is efficient in handling constraint problems for the global optimization of various problems. However, modifications in the base algorithm have always proven to be a potential option regarding the convergence rate, attaining a global optimum solution, and improving solution quality regarding the statistical results. The present study incorporated an artificial neural network strategy with the supercell thunderstorm optimizer for further performance assessment. Figure 1 shows the enhancement of the process with the artificial neural network strategy. This strategy considers all the inputs within the search space, as inspired by the neurons of the brain, which sense each of the activities of the human body, whether external or internal, and respond accordingly by identifying the highest priority signal. Figure 1 shows the artificial neural network (ANN) augmentation process with the base algorithm.

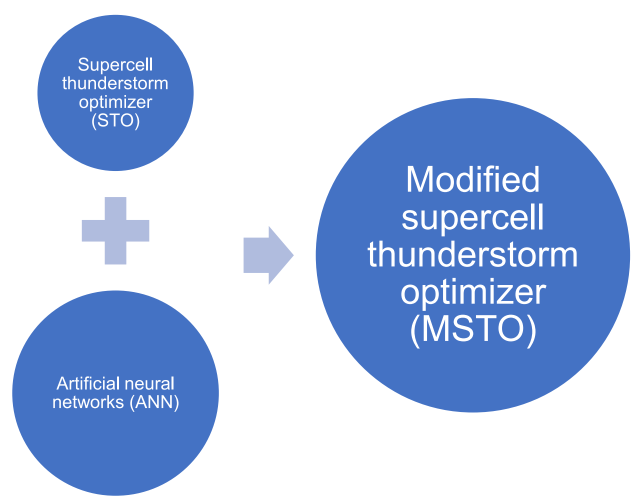

Figure 1: Modified supercell thunderstorm optimizer.

$$X_i\,(t+1) = \begin{cases} rand \times X_{\mathrm{best}}\,(t) + d_i\,(t) \times (i\,(t) - 3\,\mathrm{rand} \times X_{\mathrm{mean}}\,(t)) + y_i\,(t) \times (x_i - 2 \times X_{\mathrm{best}}\,(t))), r_7 \leq 0.3 \\ X_i\,(t) + \mathrm{rand}[X_{\mathrm{best}}\,(t) - X_k\,(t)] + \mathrm{rand} \times (X_i\,(t) - X_k\,(t)), r_7 > 0.3 \end{cases} \quad (4)$$

3 Application of modified-supercell thunderstorm optimizer

In the present section, the modified ANN-based optimizer is applied to various constraints engineering discipline problems. Moreover, the results are mapped in terms of the statistical results realized by the other metaheuristics algorithms from the standard literature.

3.1 Structural optimization of a cantilever beam

The cantilever beam is depicted in Figure 2. The goal function is to reduce the structural mass of the beam [45].

The comparison of the best MSTO results with those from the literature is shown in Table 1. It has been proved that MSTO gives superior results to those seen in the literature. The lowest weight achieved was 1.3381.

3.2 Production cost optimization of industrial grinding machine

The performance of MSTO is evaluated further. Wen et al. [60] discuss a real-world grinding optimization problem for testing the proposed algorithm. Figure 3 shows the schematic illustration of the grinding machine.

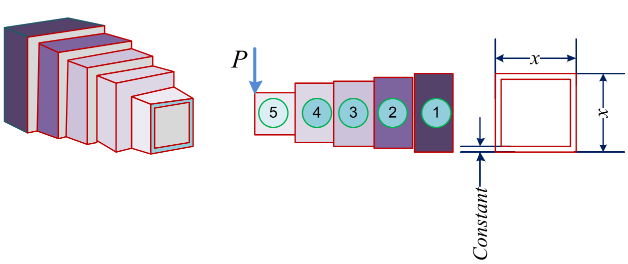

Figure 2: Beam with load and dimensional variables.

Table 1: Best results in terms of fitness function and optimized design variables comparison.

Algorithms	Fitness function
MSTO	1.3381
Parrot optimizer	1.3398
Walrus optimizer	1.3413
Crested porcupine optimizer	1.3418
Spider wasp optimizer	1.3425
Dingo optimizer	1.3432

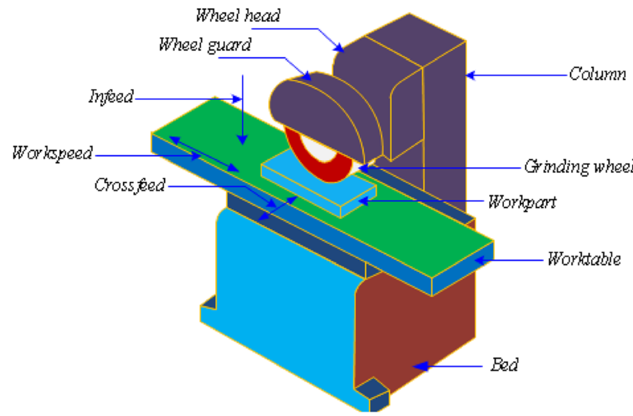

Figure 3: Grinding machine with grinding wheel and cross-feed mechanism.

Rough grinding is one of two forms of grinding that can increase production rate while reducing expenses. The second type is finishing grinding, which seeks to minimize manufacturing costs while offering the highest quality finish surface. The following is the optimization problem formulation by Wen et al. [60]. The goal of the design challenge is to minimize costs, and Equations 6–15 provide the following design constraints:

Production cost optimization as the objective function.

$$\mathrm{COF}\ (V_s, V_w, \mathrm{Doc}, L) = \frac{C_T}{C_T^*} - \frac{\mathrm{WRP}}{\mathrm{WRP}^*} + \frac{R_a}{R_a^*} \tag{6}$$

$$0 \le W_i \le 1$$

$$1000 \le V_s \le 2023 \tag{7}$$

$$10 \le V_w \le 22.7 \tag{8}$$

$$0.01 \le \mathrm{Doc} \le 0.137 \tag{9}$$

$$0.01 \le L \le 0.137 \tag{10}$$

Subject to:

$$g_1 = U - U^* \le 0 \tag{11}$$

$$g_2 = G - \frac{\mathrm{WRP}}{\mathrm{WWP}} \le 0 \tag{12}$$

$$g_3 = \frac{|\mathrm{R_{em}}|}{K_m} - \mathrm{MSC} \le 0 \tag{13}$$

$$g_4 = R_a - 1.8 \le 0 \tag{14}$$

Table 2 compares the outcomes reported in the previous articles and those achieved utilizing MSTO. Table 2 clarifies that the MSTO finds a global optimum with 10.000 function evaluations.

3.3 Optimization of tubular column design for cost minimization

Here, the goal function is subject to several restrictions. Design variables are given in Figure 4. The best-achieved objective function values and superior decision variable values for each algorithm are shown in Table 3. In contrast, Table 4 provides important statistical information about the optimizers. MSTOA achieves a higher quality result in this case study than the other optimizers.

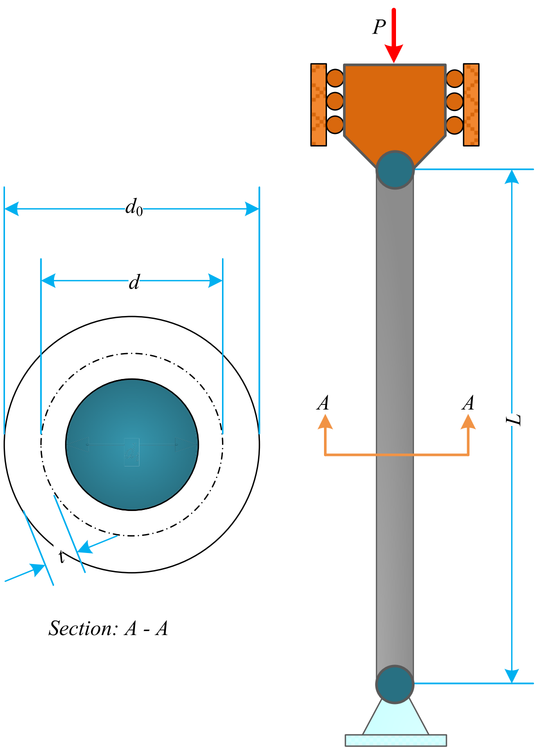

Figure 4: 3-D model of tubular column.

Table 2: Best results in terms of fitness function and optimized design variables comparison.

Method	COF	NFE
GOA [5]	−0.22925	30.000
MVO [5]	−0.22925	30.000
HHO [5]	−0.22925	27.000
GTO	−0.22925	30.000
WOA [38]	−0.22925	32.000
HWOANM [38]	−0.22925	20.000
MSTO	−0.22925	10.000

3.4 Weight optimization of the spring

Any mechanical system must have springs, which are often employed to absorb stress. It is exposed to a tensile force P, as seen in Figure 5. Furthermore, the primary goal of this study is to reduce the spring's weight while taking stress and deflection into account. As a result, Table 5 displays the statistical findings from MSTOA and six previously evaluated methods documented in the literature. The fact that MSTO's can achieve the best-optimized fitness function values with the fewest variations.

3.5 Global optimization of fin and tube heat exchanger (FTHE)

With a broad heat duty capability, heat exchangers (HEs) are well-known heat recovery machines in several sectors. Additionally, FTHE's expanded surface area over the cylindrical tube increases the heat transmission rate. FTHEs are typically composed of stainless steel and aluminium. Both longitudinal and transverse augmentations are possible for the fins. The FTHE is used explicitly in industry for process heating purposes. Figure 6 displays a crisp three-dimensional view of FTHE. The optimization of the FTHE considers the particular application, which is to lower the temperature of the water-processed air. The heat exchanger's overall cost is optimized and chosen as the goal function. Therefore, the FTHE's initial cost, as well as any maintenance or handling costs, are taken into account when calculating the final economic factors.

The economic optimization of the FTHE was examined in this article using a unique modified-supercell thunderstorm optimization algorithm. The statistical findings from the MSTOA and eight other MHs that were compared are shown in Table 6. Table 6 shows that MSTOA achieves the best outcomes (at the lowest cost) with a noteworthy success

Table 3: Best solutions obtained by the applied algorithms on the tubular column problem.

Variables	Algorithms					
	MSTOA	Walrus optimizer	Crested porcupine optimizer	Spider wasp optimizer	Dingo optimizer	Parrot optimizer
f_{best}	26.5313	26.60005	26.54384	26.53933	26.53155	26.53145

Table 4: Comparison of various statistical values by the applied algorithms on the tubular column problem.

Algorithms	Best	Mean	Worst	SD
Walrus optimizer	26.60005	26.8612	27.2122	0.15423
Crested porcupine optimizer	26.54384	26.6834	26.8652	0.09234
Spider wasp optimizer	26.53933	26.6325	26.8621	0.067521
Dingo optimizer	26.53155	26.5378	26.5455	0.002345
Parrot optimizer	26.53145	26.5358	26.5435	0.004532
MSTOA	26.53130	26.5312	26.5315	0.000012

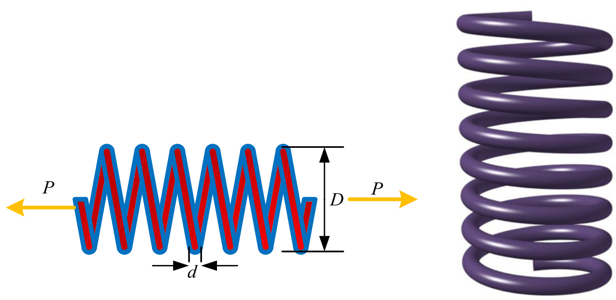

Figure 5: 3-D plot of helical coil spring.

Table 5: Statistical findings for the helical coil spring.

Optimizers	Best values	Mean values	Worst values	Deviations
MSTOA	0.01265	0.012658	0.012700	1.21E−03
Parrot optimizer	0.01269	0.01271	0.01272	1.27E−03
Walrus optimizer	0.01273	0.01274	0.01275	1.81E−03
Crested porcupine optimizer	0.01274	0.01275	0.01276	1.63E−03
Spider wasp optimizer	0.01275	0.01276	0.01277	1.94E−03
Dingo optimizer	0.01275	0.01277	0.01278	1.38E−03

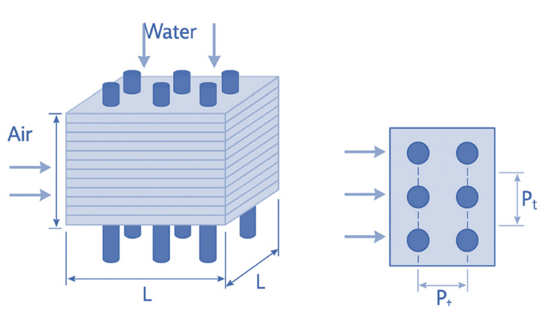

Figure 6: Fin and tube heat exchanger layout.

Table 6: Results and comparison with literature statistics.

MHs	Best value (least total cost)	Worst value	Mean value	SD-standard deviation
MSTOA	3,466.57	3,466.894	3,467.586	0.0000489
Parrot optimizer	3,466.97	3,470.93	3,468.63	1.17
Walrus optimizer	3,466.91	3,470.45	3,467.73	1.30
Crested porcupine optimizer	3,466.91	3,468.55	3,467.01	0.365
Spider wasp optimizer	3,466.93	3,470.77	3,468.59	1.73
Dingo optimizer	3,466.91	3,470.45	3,467.59	1.29

rate. Additionally, it can be verified that the MSTOA's target standard deviation is significantly lower than that of the findings of the FTHE problem.

3.6 Global optimization of automobile components

The vehicle diaphragm spring was structurally optimized in this part to lower the component's total weight. Because it is an essential part of any car system that loads, absorbs energy, and delivers efficient comfort drive. As a result, it experiences complicated strains and unequal loads, which cause the diaphragm spring to break. Equations 15 and 16 provide the fitness function and limitations in mathematical form.

Minimization of mass of spring.

$$F(y) = \text{mass}(y) \tag{15}$$

Imposed Constraint.

$$g(y) \le 0, \tag{16}$$

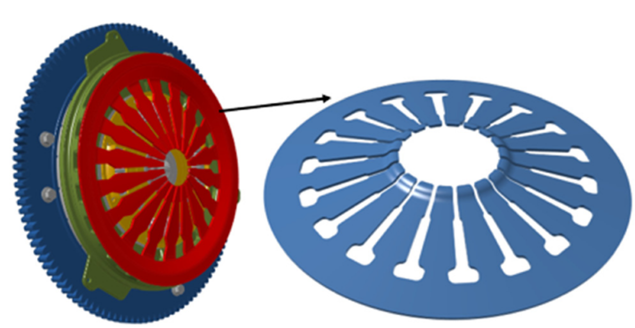

Figure 7: Initial design of the spring.

Figure 8: Constraint on component.

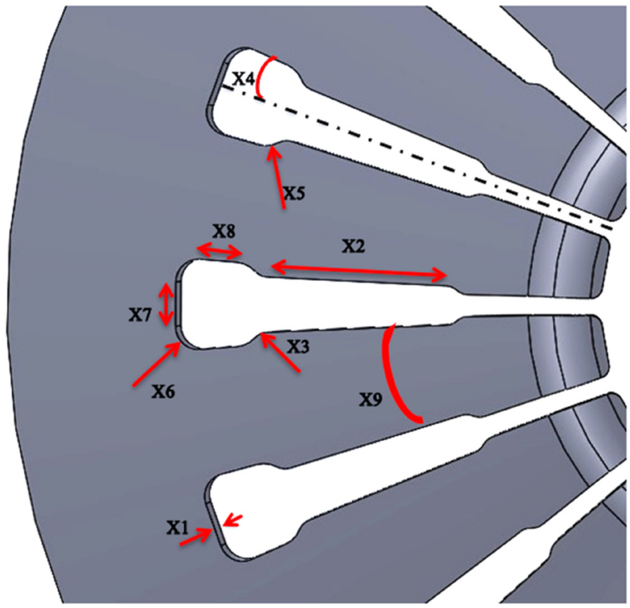

Figure 9: Design variables.

Figure 10: Globally optimized design.

$$y_i^{\mathrm{l}} \le y_i \le y_i^{\mathrm{u}}, i = 1$$

As a result, Figures 7 and 8, respectively, show the diaphragm spring's original design and limiting circumstances.

Design parameters of the spring's diaphragm are discovered for possible optimization using MHOA in this study. Additionally, each parameter has the following bounds: $1 < Y_1 < 8$, $20 < Y_2 < 40$, $1 < Y_3 < 6$, $1 < Y_4 < 4$, $1 < Y_5 < 9$, $2 < Y_6 < 7$, $1 < Y_7 < 7$, $1 < Y_8 < 10$, and $10 < Y_9 < 20$. Furthermore,

Table 7: Results for the automobile component.

Optimizer	Optimized-mass (g)	Stress-constraints (MPa)
Initial design	917.2	489
Walrus optimizer	653.7	765
Crested porcupine optimizer	648.8	767
Spider wasp optimizer	632.7	782
Dingo optimizer	627.5	780
MSTOA	610.8	778

Figure 9 shows each of the design variables. As a result, Figure 10 displays the system's structurally optimized design utilizing MHOA. Table 7 tabulates the algorithm's statistical results after comparing them to those of HOA and four other well-known algorithms. Nevertheless, when it came to the best-optimized outcomes with the fewest functional evaluations, MHOA outperformed other algorithms. Mass of the spring is reduced from 917.2 g to 610.8 g.

4 Conclusions

In this work, a modified supercell thunderstorm optimizer (MSTO) combined with an ANN strategy was proposed and successfully applied to various real-world constrained engineering optimization problems. The integration of ANN improved the optimizer's capability to explore the search space more intelligently and converge efficiently towards global optima. The performance evaluations on problems such as cantilever beam structural optimization, industrial grinding cost reduction, tubular column design, and spring weight minimization revealed that MSTO consistently outperformed traditional metaheuristic algorithms in terms of solution quality, computational efficiency, and robustness. The results validate the effectiveness and potential of MSTO as a promising tool for complex industrial optimization tasks.

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Conflict of interest: The authors state no conflict of interest.
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