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PARAMETER OPTIMIZATION OF TRACTOR'S STEERING TRAPEZOID MECHANISM BASED ON IMPROVED ADAPTIVE DIRECTION STRATEGY TEACHING-LEARNING-BASED OPTIMIZATION

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KEYWORDS

Tractor, steering trapezoid mechanism, optimization, feedback stage, teaching-learning-based optimization

ABSTRACT

The parameter optimization of the tractor's steering trapezoid mechanism is a traditional optimization problem, and the teaching-learning-based optimization (TLBO) has a better solving ability for parameter optimization of the tractor's steering trapezoid. However, the teacher stage and student stage of TLBO limit the accuracy and stability and the ability to jump out of the local optimization solution. To obtain an optimal solution with an higher accuracy, an improved adaptive direction strategy teaching-learning-based optimization (IADS-TLBO) was used. This improved the feedback stage based on the adaptive direction strategy teaching-learning-based optimization (ADS-TLBO). The IADS-TLBO was verified by three different testing functions, and the results showed that the improved ideas are valid and feasible. Finally, the IADS-TLBO was used to optimize the steering trapezoid mechanism of JOHN DEERE T600. The optimal parameters obtained were as follows: the bottom angle was 35.4°, and the steering arm length was 154 mm. A verification experiment was conducted in the farm tool laboratory of Northeast Agricultural University (China). The experimental results showed that the average bottom angle was 35.48°, and the relative error between the measured and optimized bottom angles was 0.23%, which is less than 5%. This result showed that the results obtained by IADS-TLBO were reliable.

INTRODUCTION

The parameter optimization of the tractor's steering trapezoid mechanism is a constrained optimization problem. The nonlinear optimization model established for practical problems has many problems, such as multiple variables and multiple optima, and the objective function is complex. The traditional methods (complex method, gridding method) have difficulty in solving these problems (Wang et al., 2018). The heuristic intelligent optimization algorithm is an active research topic in artificial intelligence because it only depends on computing ability to solve the constrained optimization problem without considering the complexity of the optimization problem. In recent years, many heuristic intelligent algorithms have been designed and applied to optimize the parameters of tractor's steering trapezoid mechanism which include the genetic algorithm (Zhao et al., 2017; Wang et al., 2018; Wang et al., 2015), particle swarm optimization (PSO) (Liu et al., 2013), ant colony optimization (Liang & Guan, 2013), artificial bee colony (Karaboga & Akay, 2009), and fireworks explosion optimization (Pan et al., 2009; Xie et al., 2016). Practices have shown that a heuristic intelligent algorithm is effective in solving the tractor's steering trapezoid. However, these algorithms have the general characteristic that some special parameters need to be determined in the solving process. Furthermore, the precision of such parameters seriously affects the efficiency and this can even determine whether the algorithm can solve the optimization problem at all. Therefore, these shortcomings limit engineering applications in some fields.

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Teaching-learning-based optimization (TLBO) was proposed to realize the evolution of the population by simulating the teaching and the learning between teachers and students. Compared with traditional intelligence optimization algorithms, TLBO has the advantages of having fewer parameters, a simple structure, easy implementation, and fast solution speed (Niknam et al., 2012). This algorithm has been widely used in cooling and heating device optimization (Rao & Patel, 2013), mechanical design optimization (Rao et al., 2011), secondary assignment problems (Dokeroglu, 2015), image retrieval (Bi & Pan, 2017) and other problems. Similar to other intelligence optimization algorithms, TLBO tends to fall into a local optimum, and the convergence speed and accuracy of the algorithm are not ideal when solving high-dimensional and multipeak complex problems. To overcome these shortcomings, many improvements have been made and applied. These advances have improved the accuracy of the algorithm, its convergence speed and the ability to jump out of the local optima. In this connection, Bi & Pan proposed an adaptive teaching optimization algorithm based on a hybrid strategy, which used a comprehensive crossover learning strategy and perturbation strategy using multiple factors to prevent the algorithm from falling into a local optimum prematurely. Bi & Pan (2017) integrated the mutation strategy of the differential evolution algorithm in the learning stage of TLBO and imported the individual disturbances in the later stage of the evolution thereby improving the optimization performance of the algorithm. Zou et al. (2017) proposed a teaching optimization algorithm based on local learning and repulsive learning. The algorithm added a self-learning method combined with historical information and a regrouping operation based on a certain algebra. However, the solution accuracy is low, the later convergence speed is slow, and the evolution process easily falls into the local optimum. All these are the main problems of TLBO and the later improved algorithms. Thus TLBO still has much room for improvement.

This paper selects the parameter optimization of tractor's steering trapezoid as the research objective, and an improved adaptive direction strategy teaching-learning-based optimization (IADS-TLBO) is proposed based on the TLBO. The IADS-TLBO increases the directional adaptive feedback learning to improve the accuracy, stability and ability to jump out of the local optimum. The validity of the improved algorithm was verified by three test functions. Finally, the improved algorithm was applied to optimize the parameters of the tractor's steering trapezoid, and the reliability and feasibility of the optimization result were verified experimentally.

MATERIAL AND METHODS

Improved adaptive direction strategy teaching-learning-based optimization (IADS-TLBO)

Teaching-learning-based optimization

The supervised learning algorithm is a new population-based simulation algorithm. It imitates the two basic processes of the traditional teaching and learning phenomena: one is to acquire new knowledge from the tutor, which is called the teacher stage. The other is to obtain new knowledge by communicating with other students, which is called the student stage (Li, 2004; Zhao, 2006; Rao et al., 2011). All the learners are considered to be a population for the population-based simulation algorithm. The solution of the objective function contains different variables and corresponds to different courses that the student has learned. The fitness value corresponding to the objective function is regarded as the course score of different students, and the optimal solution in the entire population is regarded as the tutor of the population.

(1) Teacher stage

The teacher stage imitates the teaching process in reality. Suppose M_i is the average of the entire population in the i^{th} iteration, X_j is an individual (student) in the whole population, and X_{best} is the best individual in the whole population. The teacher increases the level of each individual by increasing the mean value of the whole population. The learning ability of each student is determined as follows:

$$\text{Difference\_Mean}_j - r_j(X_{\text{best,i}} - T_F M_i) \tag{1}$$

Where:

r_j is a random number in (0,1), which denotes the index of students' learning ability;

T_F is the teaching influence factor, which denotes the index of tutors' teaching ability. The value of T_F is 1 or 2 and can be determined as follows:

$$T_F = round(1 + rand(0, 1)) \tag{2}$$

According to [eq. (1)], the individual is updated as follows:

$$\mathrm{X}_{new,j} = \mathrm{X}_{old,j} + \text{Difference\_Mean}_j \tag{3}$$

Where:

$X_{old,j}$ is the j^{th} original individual in the whole population and $X_{new,j}$ is the updated individual for $X_{old,j}$. If $X_{new,j}$ has a better fitness than $X_{old,j}$, $X_{old,j}$ is replaced by $X_{new,j}$. The update process repeats until the whole population is updated in the teacher stage.

(2) Student stage

The student stage imitates the exchange process of students in reality. The individual improves the quality of the solution for the whole population that communicates with each other (Sun et al., 2016). For an individual of the whole population, the quality of the solution can be improved by exchanging with another if the solution of the other individual is better than it. The update process of an individual is shown as follows.

Suppose X_i, X_j are the i^{th}, j^{th} individuals of the whole population, $X_j(i \neq j)$, which is randomly selected from the whole population. If the fitness value of X_i is superior to X_j, then

$$X_{new,i} = X_i + r(X_i - X_j) \tag{4}$$

otherwise,

$$X_{new,i} = X_i + r(X_j - X_i) \tag{5}$$

As in case of the teacher stage, if $X_{new,i}$ is superior to X_i, $X_{new,i}$ is selected as the new individual. Repeating the abovementioned process, the whole population has a new update process in the learner phase. The update process repeats until the whole population is updated in the student stage.

The teaching-learning stage is repeated, and the whole population is updated. The teaching-learning process will stop when the termination condition of the algorithm is reached.

Improved adaptive directions strategy teaching-learning-based optimization

Because the learning of the teacher stage and the exchange of the student stage are carried out in a random manner, the optimum obtained by teaching-learning-based optimization is unstable, and improved solutions are obtained by increasing the population numbers or the number of iterations. After self-adaptive teacher-stage and student-stage learning with mentor-based learning algorithms, the level of the individual would to a certain extent, resulting in the level of the teacher failing to meet the requirements of the students. Thus the teacher also needs to improve his/her personal teaching ability to participate in teaching at the teaching stage.

(1) Adaptive directions strategy in the teacher stage

In the teacher stage, it is assumed that the tutor's knowledge level is the highest among all student populations, which is expressed as $f(X_{best})$. Each student has a different learning ability when the teacher teaches. Suppose λ_t^{Ti} is the learning ability of the i^{th} student individual after the t^{th} iteration. $f(X_i)$ denotes the learning ability of the i^{th} student individual. The update process of the student population is expressed as follows:

$$\lambda_t^{Ti} = \frac{f(X_i)}{f(X_{best}) + f(X_i)} \tag{6}$$

$$X_{new,i}^{(1)} = \lambda X_{best} + (1-\lambda) X_i \tag{7}$$

$$X_{new,i}^{(2)} = X_{best} + (X_{best,i} - X_{best,i}^{(1)}) \tag{8}$$

Where:

X_{best} is the tutor of the student population, and

X_i is the i^{th} student individual.

(2) Adaptive directions strategy in the student stage

In the exchange process, the student individual will learn more knowledge if he/she has a stronger learning ability, and the learning ability of the students corresponds to the fitness of the function solution. The individual of the whole population updates based on his/her fitness rather than in a random way as in TLBO. Adaptive direction strategies have many similarities in the teacher and student stages. Suppose λ_t^{Si} is the exchange influence factor of the i^{th} student individual after the t^{th} iteration.

$$\lambda_t^{Si} = \frac{f(X_i)}{f(X_i) + f(X_j)} \tag{9}$$

Where:

$f(X_i)$ denotes the fitness of X_i. There are two situations for an individual to update; if X_i is superior to X_j, the student individual updates as follows:

$$X_{new,i}^{(1)} = \lambda X_i + (1-\lambda) X_j \tag{10}$$

$$X_{new,i}^{(2)} = X_i + (X_i - X_{new,i}^{(1)}) \tag{11}$$

Otherwise, the student individual updates as follows:

$$X_{new,i}^{(1)} = \lambda X_i + (1-\lambda) X_j \tag{12}$$

$$X_{new,i}^{(2)} = X_j + (X_j - X_{new,i}^{(1)}) \tag{13}$$

If the new solution is superior to X_i, the possibility of finding a better solution from the updated individual is greatly improved, and it is easier to jump out of the local optimum.

(3) Adaptive directions strategy in the feedback stage

In the teacher stage of the adaptive direction strategy, improving the level of the whole population is the focus, and the improvement of self-ability for the tutor is ignored. This is inconsistent with the actual teaching-learning process. Hence a feedback learning process is added to the teacher stage, and the tutor improves his/her own level by communicating with students. Suppose λ_t^{Ci} is the communication impact factor between the teacher and the i^{th} student individual after the t^{th} iteration.

$$\lambda_t^{Ci} = \frac{f(X_{best})}{f(X_{best}) + f(X_i)} \tag{14}$$

Where:

X_{best} is the tutor of the contemporary population;

$f(X_{best})$ is the fitness of X_{best};

X_i is the i^{th} individual of the population, and

$f(X_i)$ is the fitness of X_i. The level of tutor is updated by

$$X_{best,i}^{(1)} = \lambda X_{best} + (1-\lambda) X_i \tag{15}$$

$$X_{best,i}^{(2)} = X_{best} + (X_{best,i} - X_{best,i}^{(1)}) \tag{16}$$

If $X_{best,i}^{(2)}$ is superior to X_{best}, X_{best} is replaced by $X_{best,i}^{(2)}$. The positional relationships of X_i, $X_{best,i}^{(1)}$, $X_{best,i}^{(2)}$ and X_{best} are shown in Fig. 1.

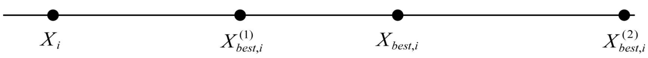


FIGURE 1. The position relationship of the updated teacher.

If all the above variables are located in a peak value of the objective function, the fitness of the updated tutor is shown in Fig. 2. It has a high possibility of obtaining a better tutor from $X_{best,i}^{(1)}$ and $X_{best,i}^{(2)}$. At the same time, because different individuals are located in different positions of the solution interval, the tutors can be constantly updated and improved. If all above variables are divided into different peaks that are similar to the single peak, the chance of obtaining the best tutor is equal.

(4) Algorithms implementing the procedures

The evolutionary process of IADS-TLBO is described below.

Step 1: Initialize, setting the parameters of the algorithm, including population size, dimension, number of iterations, length, width, and level.

Step 2: An initial population is randomly generated, the best individual is selected, and the fitness of each individual is calculated.

Step 3: Teaching stage: all individuals are updated according to eqs (6)~(8).

Step 4: Student stage: all individuals are updated according to eqs (9)~(13), saving the best individual.

Step 5: the number of iterations reach the preset number, and the optimal individual is the optimal solution. Otherwise, go to step 6.

Step 6: In the feedback stage, the self-ability of the tutor is updated according to eqs (14)~(16); let $t = t + 1$, and go to step 3.

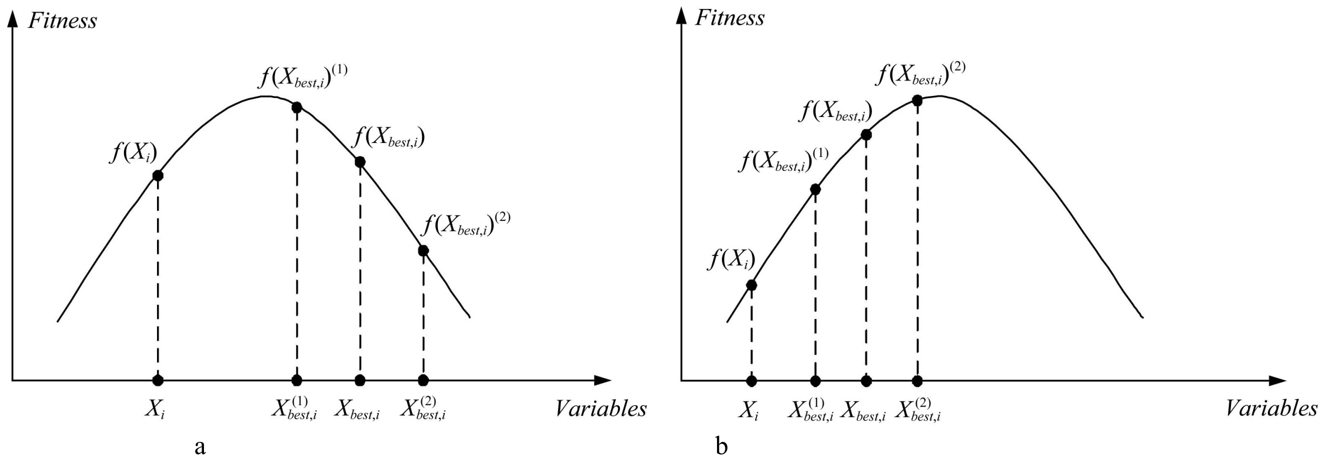
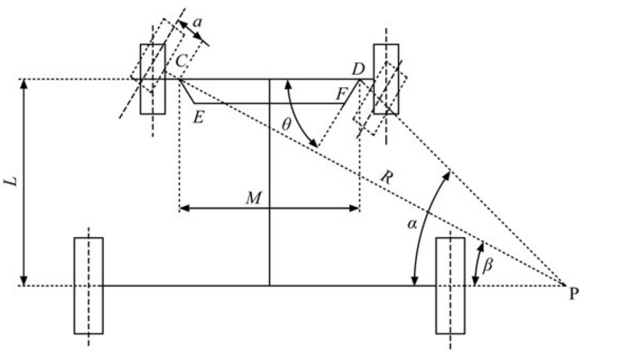


FIGURE 2. Relationship between the updated teacher and the original teacher.

Mathematical model of the tractor's steering trapezoid mechanism

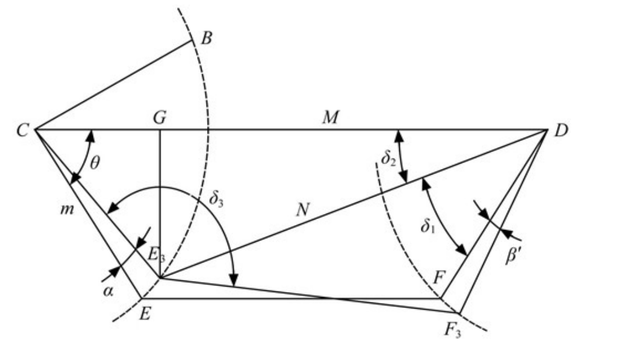
Fundamental assumption

In the steering process, the tractor's steering trapezoid mechanism exhibits a motion error between the actual movement track and the theoretical track, which increases tire wear and decreases the safety and stability of the steering. Through the optimization of the parameters of the steering mechanism, the error will be effectively reduced and the tractor's steering performance and handling safety will be improved. To minimize the error between the actual movement track with the theoretical, the weighted sum of the relative error of the theoretical rotation angle with the actual of the external front steering wheel was selected as the objective functions of structural optimization in this paper. The schematic diagram of the tractor's ideal steering process and the actual steering process are shown in Figs. 3 and 4.



Note: α is actual rotational angle of inside front steering wheel (°); β is theoretical rotational angle of external front steering wheel (°); M is the distance between the left and right vertical shafts (mm); L is distance of rear and front axle of wheel (mm); R is steering radius of external front steering wheel (mm); θ is bottom angle of steering trapezoid mechanism (°); a is distance of wheel and steering pin (°).

FIGURE 3. Theoretical steering process schematic



Note: α is actual rotational angle of inside front steering wheel, (°); M is the distance between the left and right vertical shafts (mm); θ is bottom angle of steering trapezoid mechanism, (°); β' is ideal rotational angle of external front steering wheel, (°); m is steering arm length of steering trapezoid mechanism, (mm); N is length of auxiliary line (mm); δ_1, δ_2 and δ_3 are interior angle of auxiliary calculation, (°).

FIGURE 4. Schematic of the actual steering process.

Optimization model of the tractor's steering trapezoid mechanism

We can obtain the following equation according to the geometric relationship of Fig. 3:

$$\beta = \operatorname{arccot}(\frac{M}{L} + \cot\alpha) \tag{17}$$

Where:

β is the theoretical rotational angle of the external front steering wheel, (°);

M is the distance between the left and right vertical shafts, (mm);

L is the distance between the rear and front axles of the vehicle wheel, (mm), and

α is the rotational angle inside the front steering wheel, (°).

In the process of tractor bending, when the turning radius reaches the minimum, the rotational angle of the inside front steering wheel reaches the maximum rotational angle; then,

$$\alpha_{\max} = \arctan\frac{L}{\sqrt{(R_{\min} - a)^2 - L^2} - M} \tag{18}$$

Where:

$\alpha_{\max}$ is the maximum rotational angle of the inside front steering wheel (°);
$R_{\min}$ is the minimum turning radius (mm).

Fig. 4 shows a schematic of the actual steering process when the rotational angle of the inside steering wheel is α. The dotted line represents the positional relationship of the steering trapezium mechanism when the steering is not started, as shown in Fig. 4.

$$N^2 = M^2 + m^2 - 2\text{ mM}\cos(\theta - \alpha) \tag{19}$$

Where:

N is the length of the auxiliary line (mm);

m is the steering arm length of the steering trapezoid mechanism (mm), and

θ is the bottom angle of the steering trapezoid mechanism (°).

$$S^2 = N^2 + m^2 - 2mN\cos\delta_1 \tag{20}$$

Where:

S is the length of the tie rod (mm) and δ_1 and δ_2 are the interior angles of the auxiliary calculation (°).

We can obtain the following from eqs (19)-(20) and Fig. 4:

$$\beta' = \delta_1 - (\theta - \delta_2) = \delta_1 + \delta_2 - \theta \tag{21}$$

$$\delta_2 = \arcsin\frac{GE3}{N} = \arcsin\frac{m\sin(\theta-\alpha)}{N} \tag{22}$$

Where:

β' is the ideal rotational angle of the external front steering wheel, (°).

Therefore,

$$\beta' = \arccos\frac{M^2 + 2m^2 - (M - 2m\cos\theta)^2 - 2Mm\cos(\theta-\alpha)}{2m\sqrt{m^2 + M^2 - 2Mm\cos(\theta-\alpha)}} + \arcsin\frac{m\sin(\theta-\alpha)}{\sqrt{m^2 + M^2 - 2Mm\cos(\theta-\alpha)}} - \theta \tag{23}$$

To ensure the steering performance of the tractor, the actual rotational angle function of the external front steering wheel should be as close as possible to the ideal rotational angle function in the process of tractor bending. The objective function of steering trapezoidal structure optimization is hence as follows:

$$\min(F(X)) = \min(\sum_{\alpha=1}^{\alpha_{\max}} \left|\beta - \beta'\right| \omega(\alpha)) \tag{24}$$

Where:

$\omega(\alpha)$ is weighting function. The computational method is as follows:

$$\omega(\alpha)=\begin{cases}1.25, & 1\le\alpha\le10\\ 0.90, & 10<\alpha\le20\\ 0.45, & \alpha>20\end{cases} \tag{25}$$

The design variables selected by the objective function are the steering trapezoidal bottom angle θ and the trapezoidal arm length m, let $\boldsymbol{X}$=[m,θ]. According to the design experience of the literature, the constraint conditions of the steering trapezium mechanism are

$$0.11M\le m\le 0.15M \tag{26}$$

$$\arctan\frac{1.2L}{M}\le\theta\le4\pi/9 \tag{27}$$

$$\frac{(M-2m\cdot\cos\theta)^2-M^2+2Mm\cos(\theta+\arcsin\frac{L}{R_{\min}-a})}{2m\cdot(M-2m\cdot\cos\theta)}-\cos(7\pi/9)\le0 \tag{28}$$

Method for detecting the steering angle of the tractor

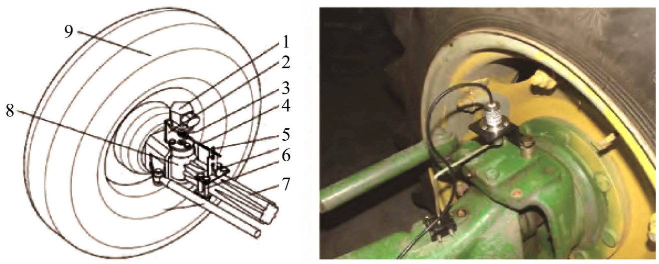
Sensor selection

To test the correctness and feasibility of the optimized design results, a new type of magnetic sensing element was used to convert the mechanical rotation into electrical signal change output, and the tractor's rotation angle was measured without contact. The sensor used in the experiment was a WYH-3 noncontact angle sensor. This avoided the influence of the working environment and mechanical vibration on the photoelectric angle sensor and displacement sensor and was suitable for measuring the steering angle of agricultural machinery. The sensor is shown in Fig. 5.

FIGURE 5. WYH-3 type noncontact angle sensor.

Sensor conformation

The WYH-3 sensor was installed on the steering column of the left front wheel of the tractor. One part of the sensor was installed at the static position relative to the body, and the other part was installed at the position that can rotate with the wheel. It can be simplified that two front wheels of the tractor are directly installed on the same front axle, and the center of the front axle is connected with the hinge of the body. The nonrotating part of the upper end of the sensor was tightly connected to the front axle of the tractor, and the rotating axle of the sensor was fastened to the rotating wheel part of the tractor, as shown in Fig. 6a. The installation position is shown in Fig. 6b.



a. b.

1. WYH-3 angle sensor; 2. Sensor base; 3. Coupling; 4. Connecting rod; 5. Connecting rod position adjusting piece; 6. Connecting rod bracket; 7. Steering shaft; 8. Front wheel steering column; 9. Front wheel;

FIGURE 6. Sensor installation diagrams.

Detection method

A dial with scale was used to measure the steering angle of the tractor's front wheel to avoid the measurement error caused by the plane movement of the contact point between the wheel rotation and the ground (Zhang et al. 2019). During the test, the driver, depending on experience, placed the tractor equipped with the sensor along a straight line and believed that the front wheel position at this time was the 0° position of steering. The sampling value output was recorded by the sensor at this time, the front wheel was turned to the limit position to the left, and the sampling value output was recorded by the sensor. Using the same method as above, the front wheel was turned to the right to the limit position, and the corresponding value was recorded.

RESULTS AND DISCUSSION

Algorithmic testing and analysis

To verify the feasibility and correctness of IADS-TLBO, three different typological functions were selected as the test functions.

Function 1:

$$\begin{aligned} &\min f_1(x) = \prod_{j=1}^{2}\left\{\sum_{i=1}^{5} i\cos[(i+1)x_j + i]\right\} + 0.5(x_1 + 1.42513)^2 + (x_2 + 0.80032)^2 \\ &s.t. \qquad -10 \le x_1, x_2 \le 10 \end{aligned} \tag{29}$$

Equation (29) was a multifunction with 760 local optimal solutions but only had one global optimum. The optimal solution was x^* = (–1.42513, –0.80032), and the optimal value was $f(x^*)$ = –186.7309 (Wang et al., 2016; Cheng et al., 2021).

Function 2:

$$\begin{aligned} &\max f_2(x) = \left(\frac{3}{0.05 + x_1^2 + _2^2}\right)^2 - (x_1^2 - x_2^2)^2 \\ &s.t. \qquad -5.12 \le x_1, x_2 \le 5.12 \end{aligned} \tag{30}$$

The optimal solution of [eq. (30)] was surrounded by different solutions, and there were four local optimal solutions distributed in the boundary of the global optimization solution. Therefore, the global optimization was difficult to obtain. The optimal solution of this function was x^*=(0,0), and the optimal value was $f(x^*)$=3600 (Sun et al., 2014).

Function 3:

$$\begin{aligned} &\min f_3(x) = -\sum_{i=1}^{2} x_i \sin\sqrt{|x_i|} \qquad i = 1,2 \\ &s.t. \qquad -500 \le x_1, x_2 \le 500 \end{aligned} \tag{31}$$

The function had symmetry and severability, and the global optimal solution was located at the boundary of the feasible region, which was far from the suboptimal solution. The optimal solution was x^*=(420.968, 420.968), and the optimal value was $f(x^*)$= –837.9658 (Yu et al., 2014).

The algorithm testing program was carried out by MATLAB R2010a, which was calculated on the processor for an AMD A8-4555 M CPU with Radeo™ HD Graphics, 64-bit Windows7 operating system. The algorithm analysis selected the ADS-TLBO as the comparison algorithm, and the relevant parameters were set as follows. The initial population number was N = 50, and the maximum generation number was set as G = 300. To verify the validity and stability of the algorithm, two termination conditions were set. One was that the error of the iteration optimal solution with a known optimal solution met the preset accuracy of 10^{-6}, and the other was that the iteration number reached the maximum generation. The testing results are shown in Table 1.

TABLE 1. Testing results of different algorithms.

Functions	Algorithm	Optimum value	Mean	The worst value	Variance
f_1	ADS-TLBO	–186.7309	–186.7119	–186.3405	0.048
	IADS-TLBO	–186.7309	–186.7309	–186.3406	0.0015
f_2	ADS-TLBO	3600.0000	3600.0000	3600.0000	7.0063e-14
	IADS-TLBO	3600.0000	3600.0000	3600.0000	2.86003e-21
f_3	ADS-TLBO	–837.9658	–837.9658	–837.9658	1.61884e-11
	IADS-TLBO	–837.9658	–837.9658	–837.9658	2.53283e-20

As shown in Table 1, the IADS-TLBO algorithm has higher accuracy and stability under the same conditions for solving the constrained problem. Compared with the ADS-TLBOA, the IADS-TLBO algorithm has better convergence, higher stability and better ability to jump out of the local optimal solution. The improvisation ideas are correct, and the algorithm is feasible.

Parameter optimization of the tractor's steering trapezoid mechanism

Optimization calculation

JOHN DEERE T600: The IADS-TLOA was used to optimize the steering trapezoid mechanism of the JOHN DEERE T600. The initial population was N=50, and the maximum generation number was G=300. The parameters of the steering arm length, bottom angle, and objective function are shown in Table 2. The optimized value was obtained by 200 generations, and the ideal value was the actual value of the objective function that the tractor's steering trapezoidal mechanism was designed.

TABLE 2. Optimal value of tractor's steering trapezoidal mechanism.

	L (mm)	M (mm)	m (mm)	θ (°)	$F(X)$
Original	2435	1202	175	36.7	1.8
Postoptimality	-	-	154	35.4	1.3

Steering characteristic analysis

To observe and verify the difference between the steering characteristic curve and the ideal Ackerman curve before and after the optimized design, the steering characteristic curves were drawn by MATLAB R2010a, as shown in Fig. 7.

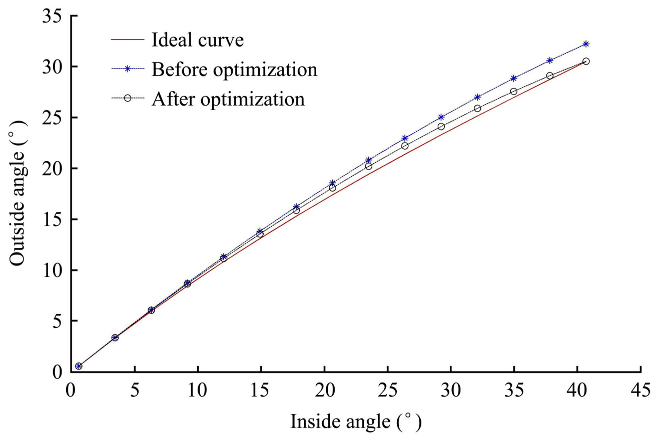


FIGURE 7. Curves between the outside and inside angles.

Fig. 7 shows that when the wheels turn to the left, as the inner wheel angle increases, the outer wheel angle also increases. Comparing the steering characteristic curves before and after optimization, it can be found that the steering characteristic curve after optimization was closer to the ideal steering characteristic curve than that before optimization. This indicated that the wear of tires during wheel turning would be reduced after optimization.

Experimental verification

To verify the correctness and feasibility of the optimization results, a tractor steering angle measurement experiment was carried out on March 20, 2022, at the agricultural test base of Heilongjiang Bayi Agricultural University, Daqing City, Heilongjiang Province, China. The test farmland ground was flat, the soil hardness was 1100 kPa, the length was 200 m, and the moisture content was 36%. To ensure the test accuracy, repeated measurements were made 20 times. The test results are shown in Table 3.

TABLE 3. Test results of the postoptimality parameter.

Method	Index	Steer angle (°)
	Minimum	35.17
Experiment	Maximum	35.81
	Mean	35.48
IADS-TLOA	Optimum value	35.4
Relative error		0.23%

Table 3 shows that the test value of the validation test was close to the theoretical value, the average relative error was 0.23%, the maximum relative error was 1.16%, the minimum relative error was –0.64%, and the error range was within the allowable range. Verification test results showed that the optimized steering trapezoid met the design requirements. Thus the optimization results obtained by this method can be used to guide the optimization of the product design.

CONCLUSIONS

In this paper, an improved adaptive directions strategy teaching-learning-based optimization (IADS-TLBO) is proposed for solving nonlinear optimization problems. This strategy increases the feedback stage based on the adaptive direction strategy teaching-learning-based optimization. In the feedback stage, the algorithm improves the self-level of the tutor by strengthening the exchanges between the teacher and student and the fitness links with the process of learning and communication. This avoids the random operation in the process of learning and communication of TLBO thereby ensuring stability, enhanced global optimization and the searching ability of the algorithm.

The IADS-TLBO was applied to optimize the tractor's steering trapezoid mechanism of JOHN DEERE T600. The performance comparison experimental results indicated that the relative error of the ideal value with the objective function calculated by IADS-TLBOA was 0.23%. The optimization result showed that the IADS-TLBO was feasible and that the optimization result satisfied the design requirements of the project.

The optimization design method of the steering trapezoidal mechanism adopted in this article can be extended to the optimization of the integral steering trapezoidal mechanism of other wheeled agricultural machinery.

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REFERENCES

Bi X, Pan T (2017) Relevance feedback image retrieval based on teaching-learning-based optimization. Acta Electronica Sinica 45(7):1668-1676.

Cheng Z, Song H, Wang J (2021) Hybrid firefly algorithm with grouping attraction for constrained optimization problem. Knowledge-Based Systems 220:1-30.

Dokeroglu T (2015) Hybrid teaching-learning-based optimization algorithms for the quadratic assignment problem. Computers & Industrial Engineering 85:86-101.

Karaboga D, Akay B (2009) A comparative study of artificial bee colony algorithm. Applied Mathematics and Computation 214(1):108-132.

Li M (2004) Research on application of data mining in auxiliary decision system. Microcomputer Information 20(5):96-97.

Liang Y, Guan H (2013) Medium-voltage distribution network planning based on improved ant colony optimization integrated with spanning tree. Transactions of the Chinese Society of Agricultural Engineering 29(S1):143-148.

Liu L, Yan G, Lei Y, Xiao D, Tang X (2013) Optimization design of steering trapezoid mechanism based on improved particle swarm optimization. Transactions of the Chinese Society of Agricultural Engineering 29(10):76-82.

Niknam T, Azizipanah-Abarghooee R, Narimani M R (2012) A new multi objective optimization approach based on TLBO for location of automatic voltage regulators in distribution systems. Engineering Applications of Artificial Intelligence 25(8):1577-1588.

Pan F, Chen J, Xin B, Zhang J (2009) Analysis of some characteristics of particle swarm optimization. ACTA Automatic Sinica 35(7):1010-1016.

Rao RV, Savsani V, Vakharia DP (2011) Teaching-learning-based optimization: a novel method for constrained mechanical design optimization problem. Computer- Aided Design 43(3):303-315.

Rao RV, Patel V (2013) Multi-objective optimization of two stage thermoelectric cooler using a modified teaching-learning-based optimization algorithm. Engineering Applications of Artificial Intelligence 26(1):430-445.

Sun X, Wang F L, Wen S (2014) An improved evolutionary strategy of genetic algorithm and a new method on generation of initial population when using genetic algorithms for solving constrained optimization problems. International Journal of Hybrid Information Technology 9(10):331-344.

Sun X, He M, Kong L, Qi H (2016) A study on adaptive direction teaching-learning-based optimization algorithm. International Journal of u-and e-Service, Science and Technology 9(4): 331-340.

Wang F, Zhu H, Wang J, Wen S (2015) An improved evolutionary strategy for genetic algorithms. Journal of Biomathematics 30(1):69-74.

Wang J, Ersoy O K, He M, Wang F (2016) Multi-Offspring Genetic Algorithm and Its Application to the Traveling Salesman Problem. Applied soft computing 43:415-423.

Wang J, Cheng Z, Ersoy O K, Zhang P, Dai W, Dong Z (2018) Improvement analysis and application of real-coded genetic algorithm for solving constrained optimization problems. Mathematical Problems in Engineering 8:1-16.

Xie C, Xu L, Zhao H, Xia X, Wei B (2016) Multi-objective fireworks optimization algorithm using elite opposition-based learning. Acta Electronica Sinica 44(5):1180-1188.

Yu K, Wang X, Wang Z (2014) Elitist teaching-learning-based optimization algorithm based on feedback. Acta Automatic Sinica 40(9):1976-1983.

Zhang Z, Wang G, Luo X, He J, Wang J, Wang H (2019) Detection method of steering wheel angle for tractor automatic driving. Transactions of The Chinese Society for Agricultural Machinery 50(3):352-357.

Zhao J (2006) Learning community-cultural analysis of learning. Shanghai, East China Normal University Press.

Zhao S, Liu C, Li Q, Zhao Y (2017) Optimal design of tractor steering trapezoidal mechanism based on real genetic algorithm. International Agricultural Engineering Journal 27(3):307-313.

Zou F, Chen D, Lu R, Li S, Wu L (2017) Teaching–learning-based optimization with differential and repulsion learning for global optimization and nonlinear modeling. Soft Computing -A Fusion of Foundations, Methodologies and Applications 22(21):7177-7205.