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Application of grey wolf optimisation algorithm in parameter calculation of overhead transmission line system

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Abstract
The transmission line is the main component in the power system consisting of inductance, capacitance, and resistance. These parameters are important during the transmission line design. This research work applies a novel optimisation technique, grey wolf optimisation (GWO), to calculate the overhead transmission line parameter. The best optimal value is estimated with the control variables. Furthermore, the effect of different bundle conductors, that is, two, three, and four bundle conductors, radius, and spacing between the conductors on the transmission line is also analysed. GWO is a recently developed nature-inspired meta-heuristic algorithm. Single-phase and three-phase transmission line test systems have been adopted for testing purposes. The proposed algorithm is inspired by the command hierarchy and hunting system of grey wolves. The algorithm is applied to 14 benchmark optimisation functions with dimension and number of search agents. The results of the GWO algorithms are optimised and are superior as compared to previously applied algorithms. The proposed algorithm achieved the best optimal solutions for most of these functions that have been validated statistically. From the results, it is identified that the proposed algorithm is computationally efficient and performs significantly better in terms of accuracy, robustness, and convergence speed.

1 | INTRODUCTION

The estimation of line parameters is very important for various power applications. Methods of calculation of line parameters can be divided into offline and online methods. On the basis of tower configuration and wire type, offline methods measure line parameters. However, because of the varying loading and weather conditions during service, the measured line parameters may be inaccurate. The PMU (phasor measurement unit) measurements’ noises can cause the estimation results to deviate from their actual value [1]. The capacity of the transmission line should be suitable for accommodating fluctuating power flows. Various methods are proposed for transmission line parameter estimation. Furthermore, various network applications, including safety relay settings, fault position, and state estimation, often employ transmission line parameters in their models.

Thus, accuracy is needed to correctly calculate line parameters as it serves as a pre-requisite for an effective and efficient operation. Previously, transmission line parameters were determined based on physical features, i.e. cable form, tower geometry, and line length estimates. These parameters are vulnerable to error as the measurement overlooks constantly altering operating variables, such as aging, skin effects, air temperature, and other weather effects. Recently, there has been a trend for replacing physics-based approaches with measurement-based methods. The supervisory control and data acquisition device, the PMU, or the protective relays’ fault record, can be used for such measurements. Some methods for estimating parameters are based on fault records. A phase domain method has been proposed to classify parameters from reported fault transient records and rely on prony forecasting methods. State increase techniques need a high degree of redundancy in the calculation and subjective conventions about parameters, restricting their practical application.

Additionally, the calculation of the parameter can be carried out independently of the state estimation. An offline parameter estimation scheme is suggested with iterations for parameter estimation and states using multiple measurement snapshots. A PMU method is developed using the approximate state...
of numerous measurement snapshots to estimate the parameters. Some of the methods, as mentioned above, use multiple measurement snapshots to improve redundancy. Nevertheless, the snapshot number must be held small to fulfill the presumption that the parameters remain constant for every snapshot considered to generate a well-conditioned coefficient matrix. These conflicting conditions limit the accuracy and applicability of parameter estimation techniques based on multiple measurement snapshots. This issue can be resolved by the dynamic parameter approximation method, particularly for future grids.

Nowadays, power generation and transmission systems are operating under increasing pressure from the state and are experiencing an increase in power loss due to increasing demand, environmental and economic or financial constraints, and the competing energy industry, so there are some needs to make better demand for power. Any power system's primary goal is to distribute power with quality, reliability, and economically to its customers. Moreover, the energy system needs to manage the transmission generation and distribution of power systems because it is difficult to quickly and effectively deliver the changing demand customer.

Mathematical simulation is important for power system analysis. There are many problems with some variables having complexity in power system analysis, and thus no unique solution to these problems exists. Thus, optimisation techniques are adopted to provide solutions to these underdetermined problems. Different artificial intelligence (AI) optimisation methods are used for different issues. The main advantage of AI is to find accurate computation with minimum error. There are different AI optimisation methods used for different physical problems. The main advantage of AI is to find accurate calculations with minimum error. This research work introduces a novel approach for the simulation of transmission line parameters in the presence of multiple bundle conductors using the grey wolf optimisation (GWO) technique to achieve an accurate simulation of the transmission line parameter problem. To assess the accuracy of GWO, it is compared with various AI optimisation techniques to solve the same problem. The proposed algorithm is attempted to introduce 14 test functions for different phases. GWO is a powerful technique compared to other AIs, such as swap algorithm compare-and-swap (CAS), particle swarm optimisation (PSO), genetic algorithm (GA), tabu search (TS), and Hirschberg–Sinclair algorithm (HS), ant lion optimiser (ALO), and dragonfly algorithm (DA) [6–7]. The total cost and computational times the GWO algorithm faced were lower than those achieved by using other optimisation algorithms, with higher convergence rates and higher performance with different algorithms in terms of solution quality. The article presented an alternate approach for optimal parameters estimation of the overhead high voltage alternating current (HVAC) transmission line.

The swarm intelligence optimisation algorithm can deal flexibly and effectively with the various problems that conventional optimisation techniques cannot solve. For this reason, optimisation techniques have been widely used in many areas of study. In other words, existing algorithms give satisfactory results in solving some of the problems, but not all. As a result, several new heuristic algorithms are proposed each year, and research in this field is active. Real value GWO is a new population-based metaheuristic approach. Because the GWO algorithm is simple, flexible, and efficient, it can be applied successfully to practical applications. There are several modified versions of the GWO algorithm. For example, some people study GWO algorithm parameters or combine GWO algorithms with other heuristic optimisation algorithms. However, all these methods use binary or decimal encoders to position the grey wolf, with information limited in the individual genes. In any evolutionary algorithms, the convergence rate is given prime importance for solving an optimisation problem over solutions’ quality. In general, GWO achieves better results than other evolutionary computer technology. However, the main thrust in real-time applications is always convergence time [8–12].

An optimisation algorithm with the following characteristics is required to evaluate transmission line parameters with different bundle conductors’ configuration. This paper has the following significant contributions:

- The application of GWO in estimating transmission line parameters is the originality and innovation aspect of the proposed work.
- A new algorithm called the grey wolf optimiser (GWO) is proposed.
- Initially, GWO is tested and compared with two well-known meta-heuristics algorithms on 14 challenging test functions.
- The quantitative results show GWO’s superior convergence and coverage.
- GWO’s coverage capacity is confirmed by the qualitative results as well.
- The ability of the new methodology to estimate transmission line parameters accurately.
- Fewer control parameter numbers.
- Faster convergence features.
- Less time to compute, resulting in reduced computational complexity.
- Same parameter settings for various issues.
- The ability to not be stuck in local minima, thus exploring a broader search area.

From previous references, it is observed that some of the above features lack different evolutionary algorithms used for transmission line parameters, including low solving accuracy, poor local searchability, complex procedure, stagnation, and a large number of parameters to adjust.

2 LITERATURE REVIEW

A meta-heuristic algorithm called the GWO imitating the social (leadership) structure, and hunting behaviour of grey wolves in the wild was developed recently [13], comprising of four types of grey wolves (alpha, beta, delta, and omega). Furthermore, they are used to model approximately the leadership hierarchy that has emerged from the search for the entire group's
survival. It is noted that three elaborate manoeuvres, that is, the search for prey, the encircling of prey, and the attacking of prey, are often followed to carry out a collaborative hunt, which has been elaborated in [14]. Essentially, GWO has the following three main advantages: (i) effective exploitation and exploration; (ii) active local optimisation prevention; and (iii) promising performance in the presence of an uncertain environment, thus, achieving an increase in global optimisation compared to other traditional heuristic algorithms, for example the use of a gravitational search algorithm [15] is used to design an adaptively fast fuzzy fractional order proportional-integral-derivative controller (PID) controller for pumped storage hydro unit. In the meantime, a multi-objective optimisation algorithm based on differential evolution (DE) is proposed to optimise the size of a photovoltaic water pumping system [16]. Moreover, an artificial bee colony algorithm is used as a local search method, whereas evolutionary programming is used to enhance the feasible path determined by a set of local practices [17]. GWO has been used in many fields, for example a practical power grid is prevented from being blacked out due to faults in generation units or main transmission lines [18]. Besides, the optimum reactive power is obtained in [19] so that the loss and voltage variance can be minimised.

In contrast, the economic displacement [20] of the power systems has been obtained by hybridising GWO with crossover and mutation for improved efficiency. The loading point effect of the valve and the ramp rate limit can be effectively handled, with and without transmission loss. Moreover, the global search capability of GWO relies heavily on an acceptable trade-off between discovery and extraction [21]. This research work targets to estimate the transmission line parameters. The GWO is suggested to address the optimised transmission line parameter considering different bundle conductors, accelerating convergence rate, and avoiding the local optimum compared to the original GWO. In order to investigate the efficiency of the proposed solution, two scenarios, that is, with and without imparting control costs in the fitness function, are considered.

Nishmitha et al. [22] proposed transmission line parameters using MATLAB. Illias et al. [23] calculated the value of transmission line parameters using the finite element method. Hamour et al. [24] applied the GWO algorithm for power loss minimisation. Naveen et al. [25] suggested the bacterial foraging optimisation technique to calculate the distribution network. Qasem et al. [26] worked on the hybrid GWO for future selection. Khandelwal et al. [27] applied GWO to the transmission network expansion planning problem. Reetta [28] applied GWO in an interconnected power system for controlling the load frequency. Thanoon and Mitras [29] discussed the modified GWO algorithm by using conjugate gradient and parallel tangent algorithm optimisation methods. Many authors have applied this technique to calculate distribution losses, but we have used this GWO algorithm on transmission line parameters. In this work, we have calculated the value of inductance and capacitance for a single phase and three phases with an arrangement of different bundle conductors with different distances, using GWO. Meta-heuristic optimisation methods have become very popular over the past two decades because of their simplicity, flexibility, derivation-free, and local minima avoidance. These techniques have been mostly inspired by elementary concepts typically related to physical phenomena, animals’ behaviour, or evolutionary ideas. The methods based on swarm intelligence behaviour belong to a branch of population-based meta-heuristics. Usually, optimisation techniques bring the control parameters of the non-linear problem to the edge, whereas their mathematical methods are challenging to implement for better accuracy. So, the proposed method is a useful optimisation technique to solve non-linear problems. Moreover, the GA [30], ant colony algorithm [31], and PSO-based techniques [32] are proposed. Additionally, metaheuristic techniques have helped solve the features problem like GWO [33–34]. Differential evolution [35], dragon algorithm [36], and GWO have much accomplished [37–38] in the field of hybrid metaheuristic field [39–40]. In [41], Yang et al. designed and implemented a grid-connected photovoltaic (PV) inverter for maximum power point tracking (MPPT) using a grouped grey wolf optimiser.

Moreover, the proposed algorithm was presented to solve different engineering optimisation problems, such as optimal power flow, the control strategy for performance enhancement of HVDC-based offshore wind farms, grid-connected permanent magnet synchronous generator (PMSG)-based wind energy conversion systems, and optimum parameters of multiple Proportional Integral (PI) controllers of a grid-connected MSG driven by variable speed wind turbine [42–45].

In the present work, single- and three-phase test systems have been tested for optimal estimation of the overhead transmission line parameters, taking into account different bundle conductors. The GWO algorithm is used for the optimal estimation of transmission line parameters with other control variables. The authors also presented a new approach for the proper estimation and coordination of control variables in single and three power system networks. Here, 14 benchmark functions are considered for single- and three-phase testing purposes, based on different bundle conductors.

This paper is organised as follows: Section 3 gives an overview of the proposed methodology. Moreover, the mathematical form of the transmission line parameter is given in Section 4. In Section 5, the performance of GWO is evaluated. Finally, Section 6 concludes and provides future recommendations for the research work.

2.1 Problem formulation

The system parameters and control variables for transmission lines with a power system have uncertainties in real-time operation. Hence, there is an inaccuracy in the estimation of such parameters for the transmission lines. Moreover, the power system can always be designed to have a sufficiently low-voltage collapse probability and the largest ability margin. To cater with such random behaviour for the transmission line, optimisation is needed to get optimal transmission line parameters’ optimal values. Thus, optimal power flow (OPF) is employed for optimisation. The OPF problem is one of the most important optimisation problems for the power system analysis that estimates
Inspiration

2.2 | Problem objective

The main research objective in this research is to optimise the transmission line parameter considering the following minimal values of inductance and capacitance for single-phase and three-phase transmission line:

\[ f_{1,\text{opt}} = \min f_1(\Delta L_1, \Delta C_1) \]  

where \( \Delta L_1 \) and \( \Delta C_1 \) are changes in inductance and capacitance for a single-phase transmission line:

\[ f_{2,\text{opt}} = \min f_2(\Delta L_2, \Delta C_2) \]  

where \( \Delta L_2 \) and \( \Delta C_2 \) are changes in inductance and capacitance for a three-phase transmission line.

Minimisation of inductance and capacitance \((\Delta L_1, \Delta C_1, \Delta L_2, \text{ and } \Delta C_2)\) in a transmission line parameter is expressed in Equations (8a)–(8d). On the basis of the problem formulation, this research work proposes a technique for estimation of the transmission line parameters using the GWO method.

3 | PROPOSED METHODOLOGY

In this section, hunting techniques and the social hierarchy are modelled to develop GWO and perform an action.

3.1 | Aim and objective of the proposed method

In this subsection, the hunting technique and the social hierarchy are mathematically modelled to design GWO and perform an action.

3.2 | Inspiration

Grey wolves are said to be the apex predators that are at the top of the food chain. They want to live in a pack, and the size of the single group from 5 to 12 almost has a strict social leading hierarchy [46]. The alpha wolf is also called the dominant wolf because it should be followed by the pack [47–48]. In the mathematical model of hunting, the mechanism of GWO is based on the following:

1. tracking, chasing, moving towards prey;
2. pursuing, encircling, and harassing the prey until he will move; and
3. finally, attacking the prey.

3.3 | Social hierarchy

During mathematical modelling, make sure that the designing of GWO, we accept the best value in the alpha. Consequently, the second-best solution is beta (\( \beta \)). The third best is the delta (\( \delta \)), and the rest is omega (\( \omega \)) wolves. In this algorithm, the hunting process is done by alpha, beta, and delta, whereas the omega follows these three rules: tracking, encircling, and attacking.

3.3.1 | Tracking

In GWO, they track the grey and reach to him while hunting process as an initial step. The wolf’s behaviour can be described mathematically in Equation (2a) and Equation (2b):

\[ \vec{X}(t + 1) = \vec{X}_p(t) - A \cdot D \]  

\[ D = ||\vec{C} \cdot \vec{X}_p(t) - \vec{X}(t)|| \]  

where \( \vec{X} \) is the position of the grey wolf, and \( t \) denotes the iteration, \( \vec{X}_p \) denotes the position of the prey, \( D \) is the distance between the wolf and the prey, as in Equation (2a), \( A \) and \( C \) are the coefficients, calculated as

\[ A = 2 \cdot r_1 \cdot \vec{r} - \vec{a} \]  

\[ C = 2 \cdot r_2 \]  

\( r_1 \) and \( r_2 \) are the two random values of the vector within the range \([0,1]\).

3.3.2 | Encircling

This attacking prey describes the strategy of GWO while attacking agents. The attack behaviour, which depends on leaders and their colleagues, encircles the agent by analysing the transmission line parameters. Capacitance and inductance as subordinate to transmission line parameter as delta wolves further calculate the transmission line parameter and attack the agent. Moreover, the transmission line parameter is defined as agents’ impacts over end-users called omega and scapegoat. We can calculate by alpha, beta, and delta, which are \( \vec{X}_\alpha, \vec{X}_\beta, \) and \( \vec{X}_\delta \) updating their position as follows:

\[ \vec{X}(t + 1) = \frac{\vec{X}_\alpha + \vec{X}_\beta + \vec{X}_\delta}{3} \]  

(4a)
\[ \vec{X}_1 = |\vec{X}_2(t) - \vec{A}_1 \cdot D| \]  
(4b)
\[ \vec{X}_2 = |\vec{X}_3(t) - \vec{A}_2 \cdot D| \]  
(5a)
\[ \vec{X}_3 = |\vec{X}_4(t) - \vec{A}_3 \cdot D| \]  
(5b)
\[ D_\alpha = |\vec{C}_1 - \vec{X}_2(t) \cdot \vec{X}| \]  
(6a)
\[ D_\beta = |\vec{C}_2 - \vec{X}_3(t) \cdot \vec{X}| \]  
(6b)
\[ D_\delta = |\vec{C}_3 - \vec{X}_4(t) \cdot \vec{X}| \]  
(7a)

3.3.3 Attacking

Grey wolves finish hunting by attacking the prey when the prey stops moving. These types of processes will linearly decrease the value of \( 'a' \) in Equation (3a). During this time interval, the amount of A also changes from \([-a, a]\). On the contrary, when the amount of \(|A| < 1\), so that the wolf’s position is nearer to the position of the prey. When \(|A| > 1\) the group of wolves will go away from the prey. So, the update equation of \( 'a' \) in GWO as in Equation (7b):

\[ a = 2 - 2 \frac{t}{\text{max iter}} \]  
(7b)

where \( t \) is the current iteration and max iteration is the maximum number of iterations.

The flowchart for GWO is shown in Figure 1.

4 | MATHEMATICAL FORM OF THE PARAMETERS

This paper has discussed transmission line parameters for a single phase and three phase, respectively, and calculated the capacitance and inductance values as defined in the following mathematical model [49].

4.1 Single-phase transmission line

\[ \Delta L_1 = \sum_{i=1}^{n-1} \left( 0.2 \ln \frac{D}{G_{\text{MRL}}} \right) \text{ mH/km} \]
\[ \Delta C_1 = \sum_{i=1}^{n-1} \left( 0.056 \ln \frac{D}{G_{\text{MRC}}} \right) \text{ F/km} \]

where \( D \) is the distance between the conductor, \( G_{\text{MRC}} \) is the geometric mean radius capacitance and \( G_{\text{MRL}} \) is the geometric mean radius inductance, and \( n \) is the total number of assumptions.

5 | RESULTS AND DISCUSSION

As proof of the result, the authors have proposed a suite of GWO. This section will also present different variables for each case of conductor for single-phase and three-phase transmission lines, as in Tables 1 and 2.

The proposed algorithm is robust as compared to previous techniques. Therefore, the GWO technique has been suggested as a preferred method for calculating transmission line parameters, as mentioned in Table 3. It has the advantages of a simple concept, less adjustable two parameters, and easy implementation.
### Table 1: Transmission line simulation data

| S# | Distance between two conductors (m) | Conductor diameter (cm) | Radius (cm) | Bundle spacing (cm) | G<sub>MR</sub> (cm) |
|----|--------------------------------------|-------------------------|-------------|---------------------|-------------------|
| 1  | 5.000                               | 3.450                   | 1.725       | 300                 | 1.3434            |
| 2  | 10.000                              | 4.560                   | 2.280       | 350                 | 1.7756            |
| 3  | 15.000                              | 5.200                   | 2.600       | 400                 | 2.0248            |
| 4  | 20.000                              | 6.650                   | 3.325       | 450                 | 2.5895            |
| 5  | 25.000                              | 7.850                   | 3.925       | 500                 | 3.0567            |
| 6  | 30.000                              | 8.500                   | 4.250       | 550                 | 3.3999            |
| 7  | 35.000                              | 9.120                   | 4.560       | 600                 | 3.5133            |
| 8  | 40.000                              | 10.100                  | 5.050       | 650                 | 3.9329            |
| 9  | 45.000                              | 11.000                  | 5.500       | 700                 | 4.2834            |

GWO parameter setting

- Number of swarm size: 30
- No. of maximum iterations: 100
- No. of dimensions: 5

### Table 2: Transmission line standard data [50–51]

| Parameter                        | Used data | Unit  |
|----------------------------------|-----------|-------|
| overhead transmission line       |           |       |
| Resistivity                      | 100       | Ωm    |
| Nominal frequency                | 50        | Hz    |
| Length                           | 400       | Km    |
| DC resistance                    | 0.05648   | Ω/km  |
| Tower height                     | 20        | M     |
| Horizontal distance in case of three phase | −10,0,+10 | M     |
| voltage source                   |           |       |
| Voltage                          | 100       | kV    |
| Frequency                        | 50        | Hz    |

This paper demonstrates the applicability and efficiency of the proposed gray wolf algorithm by using it to solve various non-linear parameters and complex problems by considering the power system transmission line parameter. The proposed algorithm for the grey wolf is designed to work with any program and various profiles. It is also tested on the standard medium overhead transmission line (OHTL) to access algorithm validity and robustness. MATLAB software (2015b) solves the algorithms and tests them on a university computer with a 3.6 GHz CUP and 16 GB of RAM. The best optimal values for single phase and three phase are tabulated in Tables 4 and 5.

#### 5.1 Single-phase transmission line

Refer to Table 4, which presents the results of a single phase for different arrangements of the bundle conductor. There is a good agreement between the results obtained using the proposed algorithm and different conventional methods for the inductance calculation, as shown in Table 6.

Therefore, this shows that the proposed algorithm can calculate inductance and capacitance for a single-phase transmission line. However, the GWO algorithm method uses very little computation time, and it is very robust compared to other techniques. Therefore, the proposed technique has been suggested as a preferred method for calculating transmission line parameters, presented in Figures 3 and 4.

#### 5.2 Three-phase transmission line

Table 5 shows the result of the three-phase OHTL of several symmetrically arranged conductor configurations. For the inductance and capacitance measurement, there is good agreement between the result obtained using the GWO algorithm and the various conventional methods, as shown in Table 7. The two-conductor capacitance behaviour is similar to that of the three conductors. Thus, the proposed technique can measure inductance and capacitance for a single-phase transmission line. The GWO technique is, therefore, suitable for the estimation of transmission line parameters.

To ensure the validity of the proposed optimisation algorithm, the analysis is applied to two transmission network systems, the first is a single step, and the second is a three system. Accordingly, the GWO iteration is set to 100 to check the algorithm’s efficiency, and the number of search agents is set to 30 with 14 optimisation functions for single- and three-phase test systems. The regulating parameters of the proposed methodology are randomly chosen for 60 trials when the algorithm is running. The simulation results contrast with different techniques, such as ALO and DA to study the GWO’s output and consider various bundle conductors.
FIGURE 2  Convergence characteristic of single-phase transmission line capacitance per unit. (a) One bundle conductor, (b) two bundle conductors, (c) three bundle conductors, (d) four bundle conductors

FIGURE 3  Convergence characteristic of single-phase transmission line inductance per unit length. (a) One bundle conductor, (b) two bundle conductors, (c) three bundle conductors, (d) four bundle conductors
### TABLE 3  The optimal control parameters of different bundle conductors obtained by grey wolf optimisation in 60 runs for single phase

| Three phase          | Capacitance per unit length       | Best optimal solution obtained by GWO | Inductance per unit length       | Best optimal solution obtained by GWO |
|----------------------|-----------------------------------|--------------------------------------|----------------------------------|--------------------------------------|
| Single bundle        | −5, −5, 0.22688, −4.5154, 1.6756,| −90.2991                            | −0.13633, 0.50919, −0.83253, −1.9121,| 1.0697                              |
| conductors           |                                    |                                      | −3.2552                          |                                      |
| Two bundle conductors| 0.16502, −0.028353, −0.38607, 3.8325,| 0.023193                            | −0.0048689, 0.59194, 0.30956, 1.2794, 4.4399,| 0.66295                            |
| conductors           | −0.030792                          |                                      | −0.0051641, −0.23764, −0.17861, −0.1681,| 0.41614                             |
| conductors           | −0.00072753, 5, −0.041934, 1.3109, 0.11103| 0.12075                             | −0.0051641, −0.23764, −0.17861, −0.1681,| 0.41614                             |
| Four bundle          | −2.9355, 5, −0.15345, −2.215, 0.19516| −0.37565                            | 0.17969, −0.076083, −0.041878, −0.00011227,| 0.085861                           |
| conductors           |                                    |                                      | −0.01431                          |                                      |

### TABLE 4  The optimal control parameters of different bundle conductors obtained by grey wolf optimisation in 60 runs for three phase

| Three phase          | Capacitance per unit length       | Best optimal solution obtained by GWO | Inductance per unit length       | Best optimal solution obtained by GWO |
|----------------------|-----------------------------------|--------------------------------------|----------------------------------|--------------------------------------|
| Two bundle conductors| 0.15084, −0.0020446, 0.57367, 0.00040637, −0.10258| 0.22634                            | 0.1128, 0.02287, −0.00083968, −0.0331, −0.010738,| 0.78216                             |
| conductors           |                                    |                                      | −0.00083968, −0.0331, −0.010738,|                                      |
| Three bundle         | 0.0002513, 0.64927, 0.16326, −0.020375, −0.0020859| 0.027884                            | 0.0016384, 0.0004086, −0.0091361, −1.694e-06, 2.3496e-05,| 0.43                               |
| conductors           |                                    |                                      | −1.694e-06, 2.3496e-05            |                                      |
| Four bundle          | 1, 1, −0.018757, 0.51761, −0.48557| 0.0067042                            | 1, −1, −1, −0.38073, 0.0076602, −0.026581,| −0.57457                           |
| conductors           |                                    |                                      | −0.026581                         |                                      |

The GWO algorithm’s convergence characteristics for the three-phase transmission are presented in Figures 4 and 5. The GWO algorithm’s convergence characteristics for the three-phase transmission are presented in Figures 4 and 5.

### 5.3  Convergence curve of proposed GWO: the technique for the best optimal value generation

The GWO algorithm discusses the search, hunting behaviour, and social hierarchy of grey wolves. Due to less randomness and different numbers of individuals assigned to global and local search procedures, the GWO algorithm is simpler to use and converges more easily. To show the proposed algorithm’s efficiency, an assessment is made by running the MATLAB program code for multiple trials (> 60 times) with the proposed parameters, as shown in Tables 1 and 2.

The best optimal value for the proposed GWO approach’s objective function is shown in Tables 4 and 5. The results of the simulation clearly show that GWO produces feasible solutions considering various bundle conductors. To verify GWO efficiency, the numerical results are checked with other existing methods, namely, ALO and DA. The GWO algorithm, considering robustness, minimal computational efforts, and premature convergence rate, shows superior results over other algorithms.

Figure 2 shows the generated result from GWO for single-phase transmission capacitance per unit length with different bundle conductor at every iteration. As the number of bundle conductors increases, the capacitance per unit length for single-phase capacitance will be more, and the best optimal values are −90.149, 0.023193, 0.12075, and −0.37565, respectively.

Figure 3 shows the generated results of GWO when the number of iterations is 100, and the search agents are 30 for single-phase transmission line inductance per unit length with different conductor layout. Bundle conductors are increasing in the conductor. The inductance will be decreased in the transmission line. The best optimal values which are obtained by GWO are 1.0697, 0.69424, 0.41614, and 0.085861, respectively.

Figure 4 illustrates the output result with the best optimal value, which are 0.22634, 0.027884, and 0.0067042 for three-phase transmission line inductance per unit length with two, three, and four bundles. The values of capacitance are more significant as the number of conductors is increasing.

Figure 5 shows the result of the three-phase transmission line inductance per unit length for different conductor...
TABLE 5  Comparison of the proposed algorithm

| Properties   | Algorithm | GWO | ALO | DA | CAS | GA | PSO | HS | TS |
|--------------|-----------|-----|-----|----|-----|----|-----|----|----|
| Parameter    | Two [52]  | Two [2] [57] | Five [61] | Three [63] | Three [68] | Five [73] | Three [77] | Four [81] |
| Complexity   | [53]      | O(Itermax*NP)* O(F(s)) [58] | O(dM + MC) [61] | O(n.Dtmax) [64] | O(n^2) [69] | O (nm2) [74] | O (HMS X M + HMS X log (HMS)) [78] | O (mn2) [82] |
| Convergence  | Fastest rate [54] | Good convergence [59] | Better convergence [62] | Slow rate [65] | Fast rate [70] | Quickly rate [75] | Suffer from permanent convergence [79] | Rapidly converged [82] |
| Strength     | The balance between exploration and exploitation [55] | The balance between exploration and exploitation [57] | The balance between intensification and diversification [66] | Deal with complex fitness landscape [71] | Do not have overlapping and mutation calculation [76] | Increase the diversity of the new solutions [80] | Avoid trapped at local optimum [83] |
| Weaknesses   | Low precision [56] | High precision [60] | High accuracy [61] | Trapped in a local optimum [67] | Evaluation is relatively expensive [72] | Suffers from partial optimism [76] | Get stuck on local optimal [80] | Needs huge memory resources [83] |
### TABLE 6  The statistical results of single phase obtained by conventional method

| S#  | Distance between conductors (m) | Inductance (mH/km) | Capacitance (pF/m) | Inductance (mH/km) | Capacitance (pF/m) |
|-----|--------------------------------|-------------------|-------------------|-------------------|-------------------|
| 1   | 5                              | 1.1624            | 9.7345            | 1.1624            | 11.0619           |
| 2   | 10                             | 1.3008            | 8.8496            | 1.3008            | 9.7345            |
| 3   | 15                             | 1.3818            | 8.4071            | 1.3818            | 9.2921            |
| 4   | 20                             | 1.4392            | 7.9646            | 1.4392            | 8.8496            |
| 5   | 25                             | 1.4838            | 7.7434            | 1.4838            | 8.8493            |
| 6   | 30                             | 1.5203            | 7.5221            | 1.5203            | 8.490             |
| 7   | 35                             | 1.5511            | 7.5218            | 1.5511            | 8.488             |
| 8   | 40                             | 1.5778            | 7.5215            | 1.5778            | 8.485             |
| 9   | 45                             | 1.6013            | 7.5211            | 1.6013            | 8.482             |

Inductance and capacitance per unit length in terms of two bundle conductor

| S#  | Distance between conductors (m) | Inductance (mH/km) | Capacitance (pF/m) | Inductance (mH/km) | Capacitance (pF/m) |
|-----|--------------------------------|-------------------|-------------------|-------------------|-------------------|
| 1   | 10                             | 1.3505            | 4.2668            | 1.3462            | 4.2667            |
| 2   | 20                             | 1.4891            | 3.8858            | 1.4730            | 3.8857            |
| 3   | 30                             | 1.5702            | 3.6572            | 1.5340            | 3.6571            |
| 4   | 40                             | 1.6277            | 3.1238            | 1.5631            | 3.0857            |
| 5   | 50                             | 1.6723            | 3.4286            | 1.6472            | 3.3905            |
| 6   | 60                             | 1.7088            | 3.4284            | 1.6642            | 3.3903            |
| 7   | 70                             | 1.7396            | 3.4282            | 1.6787            | 3.3901            |
| 8   | 80                             | 1.7663            | 3.4281            | 1.6863            | 3.3900            |

### FIGURE 4  Convergence characteristic of three-phase transmission line capacitance per unit length. (a) Two bundle conductors, (b) three bundle conductors, (c) four bundle conductors
TABLE 7  The statistical results of three phase obtained by conventional method

| S# | Distance between two conductors (m) | Inductance (mH/km) | Capacitance (pF/m) | Inductance (mH/km) | Capacitance (pF/m) |
|----|-----------------------------------|--------------------|--------------------|--------------------|--------------------|
|    |                                   | Analytical method [49] | Final element method [23] |
| 1  | 10                                | 1.3505             | 4.2593             | 1.3152             | 4.3519             |
| 2  | 20                                | 1.4891             | 3.8889             | 1.4415             | 3.9815             |
| 3  | 30                                | 1.5702             | 3.6111             | 1.4987             | 3.7037             |
| 4  | 40                                | 1.6277             | 3.5185             | 1.5140             | 3.6111             |
| 5  | 50                                | 1.6723             | 3.4259             | 1.4743             | 3.4260             |
| 6  | 60                                | 1.7088             | 3.4257             | 1.6373             | 3.4258             |
| 7  | 70                                | 1.7396             | 3.4256             | 1.6320             | 3.4257             |
| 8  | 80                                | 1.7663             | 3.4255             | 1.6235             | 3.4256             |

FIGURE 5  Convergence characteristic of single-phase transmission line inductance per unit length. (a) Two bundle conductors, (b) three bundle conductors, (c) four bundle conductors

layout, and the best optimal values are 0.78216, 0.43, and −0.57457 for the three-phase inductance. The optimal solution can be approximated with the iteration of 0.1× maximum iteration.

To more clearly show the dependence of bundle conductors on the AC transmissions line, it is plotted in Figures 2–5. This trend is consistent with the hypothesis that a more bundle conductor yields larger capacitance per unit length. As a final comment, it should be noted that the environmental factor affects the AC transmission line parameter. The effect of these factors can be significantly identified in fair and fool weather.

Moreover, it can be shown that the GWO-based proposed approach is suggested to solve the problem of optimal OHTL network parameter estimation because it provides the best results compared to others.

Figure 6 shows the percentage loss reductions and all types of capacitance and inductance for single-phase and three-phase transmission line systems, considering different bundle conductors.
CONCLUSION

The parameter calculation of the OHTL power system is discussed in this paper using the proposed GWO algorithm. The algorithm was implemented to 14 test functions for the single-phase and three-phase models, respectively. The overall costs and computation times experienced when using the GWO algorithm were lower than those obtained using other optimisation algorithms, that is, CAS, PSO, GA, TS, ALO, DA, and HS, with a higher convergence rate. The obtained results verified that the exploitation of the proposed GWO algorithm is augmented among the compared algorithms. It can be concluded that the proposed GWO algorithm is competitive in exploration when compared with other algorithms.

The proposed algorithm is fast and robust for power systems. Convergence characteristic demonstrates that GWO can solve a difficult problem. The results of the proposed method are compared with the conventional technique for single phase and three phases. The results show the effectiveness of GWO for solving the transmission line parameters problem. Finally, the GWO algorithm shows superior results over other algorithms, considering robustness, minimum computational efforts, and aversion of premature convergence. By testing 14 functions, compared with the results of ALO and DA, the GWO algorithm has been greatly improved in convergence accuracy. It achieves > 90% successful ratio for all optimisation functions with 100 maximum iterations and 30 populations, which proves the effectiveness of GWO for solving complex problems. The best optimum values are 0.78216, 0.43, −0.57457, 0.22634, 0.027884, and 0.0067042 for three-phase capacitance and inductance, whereas the best optimum values for single-phase capacitance and inductance are −90.149, 0.023 193, 0.12075, −0.37565, 1.0697, 0.69424, 0.41614, and 0.22634.

We will focus on two issues for future work. On the one hand, we will further expand the application of GWO to other real-world engineering problems. On the other hand, we will develop new meta-heuristic optimisation methods to solve optimisation problems more effectively.

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