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# Transmission network planning for realistic Egyptian systems via encircling prey based algorithms

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**Abstract:** Transmission network planning problem (TNPP) is one of the pertinent issues of the planning activities in power systems. It aims to optimally pick out the routs, types, and number of the new installed lines to confront the expected future loading conditions. In this line, this study proposes a new economic model to the TNPP. The aim of the model is to find the optimal transmission routes at least investment and operating costs. Three recent algorithms called grey wolf optimization algorithm (GWOA), spotted hyena optimization algorithm (SHOA) and whale optimization algorithm (WOA) are developed to solve the TNPP. The concept of these algorithms is based on encircling prey operation. The competitive methods are investigated to find the optimal TNPP solution for two realistic Egyptian networks. The first tested network is the 66 kV West Delta Region (WDR) system while the second one is the extra high voltage (EHV) 500 kV system. Their demand forecasting is extracted forward to 2030 dependent upon the adaptive neuro-fuzzy inference system (ANFIS). Tremendous technical and economic advantages through application of the encircling prey-based algorithms to handle the TNPP.

**Key words:** Transmission network expansion planning, encircling prey based algorithms, investment cost minimization, realistic Egyptian networks

## 1. Introduction

Transmission network planning problem (TNPP) depends on information of long-term forecasts of the consumers' needs and electric power flows from and to other networks. It seeks to optimally pick out the routs, types, and number of the new inserted transmission lines in order to confront the expected future condition with the least investment cost [1–3]. In terms of the time horizons, there are Long-, medium- and short-term horizon planning categories as in [2]. These categories are characterized with different levels of uncertainty according the considered period. The planning time horizons are varied as follows: the long-term transmission expansion time horizon is greater than ten years , the time horizon for the medium transmission expansion is in the range from 5 to 10 years, and the last short term horizon planning has the least uncertainty level and time horizon less than 5 years. Also, the security of the power system must be counted in the TNPP. Mathematically, it is mainly treated as an optimization problem that belongs to non-convex, non-linear, mixed-integer family that is

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difficult to be settled for large-scale realistic transmission systems.

For handling the TNPP, various algorithms have been presented like mixed integer linear programming [4] and [5], greedy randomized adaptive search methodology [6], genetic algorithm [7], tabu search technique [8], heuristic technique [(HT) [9], particle swarm algorithm [10] and [11], evolutionary algorithm [12], and harmony search technique [13]. In [14], firefly algorithm has been presented for the TNPP where its application has been extended for Iran 400-kV transmission grid as a realistic network. Assessment of the performance of meta-heuristics to solve the multi-stage TNPP was proceeded in [15]. Also, in [2], an integer based PSO (IBPSO) were utilized in handling the TNPP. In [16], a multi-verse optimizer (MVO) has been adopted to solve the TNPP, while a binary coded structure of backtracking search optimization (BBSO) and an integer coded BSO (IBSO) algorithms have been applied for the TNPP [17]. In those papers, [2], [16] and [17], two realistic Egyptian transmission systems of 66 and 500 kV have been utilized. In [18], numerous variants of differential evolution optimizer were carried out for static and multistage TNPP and for the allocations of VAR devices in transmission networks [19] and [20].

Grey wolf optimization algorithm (GWOA), spotted hyena optimization algorithm (SHOA) and whale optimization algorithm (WOA) are three recent algorithms [21–23]. They are similar behaviours of these algorithms based on encircling prey operation. GWOA has been presented by Mirjalili et al. [21] in 2014, which simulate the technique of hunting and the social stratum of grey wolves [24]. In [25], a modified GWOA has been applied to the conventional model of the TNPP to handle the future load growth and ignoring the related operational fuel costs. GWOA was efficiently extended to different power system optimization problems such as integrated power and heat dispatch [26], economic load dispatch [27], reactive power dispatch problem [28], frequency control in multi-area power systems [29], MPPT design for photovoltaic system [30] and sizing and siting of automatic voltage regulators [31] static var compensators [32] in electric distribution network.

SHOA was presented by G. Dhiman and V. Kumar [22] in 2017, which simulates the hunting behavior of laughing hyenas. SHOA is hassling to GWOA, SHOA amended the three best leaders into a cluster of N leaders. In [33], SHOA was expanded to handle multi-objective optimization for engineering problems. In [34], SHOA has been successfully applied to optical buffer and airfoil design problems. In [35], SHOA was utilized for solving the scheduling problem of economic load power. In [36], SHOA was effectively developed for optimal allocation of distributed generators (DGs) with network reconfiguration in distribution systems. WOA has been presented by Mirjalili et al. [21] in 2016, which mimics the technique of hunting of humpback whales in nature. WOA is hassling to GWOA and SHOA in the direction of encircling the prey, but WOA has a unique behavior via the spiral bubble-net feeding to hunt their preys. In [37], WOA has been carried out for minimizing the losses in radial distribution systems. WOA has been applied for solving the installation problem of DGs in distribution networks, reactive power dispatch and unit commitment problem in [38–40], respectively. An overview of the various WOA applications to solve different optimization problems has been introduced in [41]. Another effort for planning and identifying the location of distribution transformer by modifying their location and power ratings are discussed in [42].

These algorithms are not novel since the GWOA, WOA, and SHOA have been presented in 2013, 2016 and 2017 [21–23], but they are similarly based on encircling prey operation. Despite the high resemblance between the previous algorithms in the encircling behavior, they are greatly different in the hunting and attacking operations. Added to the similar nature, these algorithms have significant competitive advantages as simple structure, adaptive control parameter, and no derivative requirement. They are distinguished with several features and successful applications in different engineering optimization problems [24–40]. In view of the above effective applications, it gives the motivation in this paper to adopt them in a comparative manner and applied for handling a developed model of the TNPP. Besides finding the minimum cost of new transmission lines, this model searches for the most economic operating point via dispatching the generators output. GWOA, SHOA and WOA are adopted in a comparative analysis for solving the TNPP. They are applied to solve the TNPP for two realistic Egyptian networks. The first is the 66 kV transmission systems of WDR system and the second is transmission network 500 kV of EHV system.

The salient contributions of the current work with respect to previous works in the area can be summarized as follows:

- An investigated planning model based on the long-term planning and operation criteria.
- Considering technical as well as economical aspects with preserving security constraints at lowest overall costs.
- Assessing the performance of the competitive algorithms in terms of statistical indices and convergence rates.
- Application of GWOA, SHOA and WOA in a comparative manner for solving the TNPP in two realistic networks from the Egyptian grid.

This paper is arranged as pursues: Section 2 extends the model of the TNPP. Section 3 puts in the adopted GWOA, SHOA and WOA for solving the TNPP. The application results are discussed in Section 4. The outcome of the application results is concluded in the last section.

## 2. TNPP model

Typically, the TNPP goal in electricity grids aims to minimise the construction costs of new transmission lines, which satisfy the expected demands of the power sector. It also includes configuration of coming generations. The solution to the issue includes the determination of the additional circuits to be constructed in electrical networks for the sake of satisfying the predicted load requirement at the cheapest rates and complying with the specified technological, reliability and budgetary requirements. It can be described as follows:

$$MinF = \sum_{i,j\in\mathbb{N}} C_{ij} N_{ij} \tag{1}$$

This objective function, in Eq. (1), is subjected to:

$$S \cdot Pf + g = d \tag{2}$$

$$|Pf_{ij}| \le (No_{ij} + N_{ij})\, Pf_{max,ij} \tag{3}$$

$$Pf_{ij} = \frac{No_{ij} + N_{ij}}{x_{ij}} (\theta_i - \theta_j) \tag{4}$$

$$lb \le N_{ij} \le ub \tag{5}$$

$$0 \le Pg_{slack} \le Pg_{slack}^{max} \tag{6}$$

In this TNPP model Eqs. (1–6), the generated from power all the generators except slack unit are enforced as fixed generation. Thus, they are treated as non-dispatchable generators with 100% renewable power penetration [42].

Another model is presented by integrating the minimization of the fuel cost related to the generated power, which is traditionally modeled as polynomial quadratic function [45] and [46]. Therefore, the fitness function of Eq. (1) is augmented with the total fuel cost function related to the generated power ( $F^*$ ) that is defined in Eq.(7) as:

$$MinF^* = Min\left(\sum_{g=1}^{N_g} a_g Pg_g^2 + b_g Pg_g + c_g\right) \tag{7}$$

For managing this fitness function, the power output from the generators are augmented as control variables as well. Thus, the inequality constraint of Eq. (6) is expanded as follows:

$$0 \leq Pg_g \leq Pg_g^{max}, g = 1, 2, .....N_g \tag{8}$$

Also, the difference between the bus voltage angles at the line sides is bounded to act as a representative for a transient stability limit as in Eq. (9):

$$0 \leq \theta_{ij} \leq \theta_{ij}^{max} \tag{9}$$

This model of TNPP has the advantage of searching for the most economic operating point besides finding the minimum cost of new transmission line to the system. Not only that but searching for minimizing the fuel costs by dispatching the generators output will have a great effect on minimizing the added lines to the systems.

Therefore, the current paper considers two models for solving TNPP as shown below:

- The first model of TNPP considers Eqs. (1–6) as similar as previous methods in the literature [2], [15] and [16].

- The second model of the TNPP considers Eqs. (1–9). This investigated model combines both objectives in (1) and (7) as augmented function.

For instance, the standard Garver system can be utilized for TNPP. Fig. 1 displays its single line diagram (SLD). It has 6-buses and 6 exit routes where each route represents one circuit [2]. As is shown, there are 15 new possible routes where five circuits can be installed in each route based on the solution of the TNPP. Based on this test system, the control variables for the first model are the circuit routes of the added transmission lines which is within range of 1–15, and the number of circuits for each selected line, which is within the range of 0–5 where zero means that no circuit is installed in that line. In this model, only the objective of the expansion costs of the new lines in Eq. (1) is to be minimized. For the second model, the outputs of the three generators, as well, are optimally dispatched to minimize the fuel operational costs of Eq. (7) for each configuration. In both models, the equality limitations of the load flow in Eq. (2), and the inequality limitations of Eqs. (5), (6), (8) and (9) should be preserved.

## 3. TNPP procedure

### 3.1. Adopted encircling prey based algorithms for the TNPP

Grey wolf optimization algorithm (GWOA), spotted hyena optimization algorithm (SHOA) and whale optimization algorithm (WOA) are encircling prey based algorithms, which simulate the technique of hunting and the social stratum of grey wolves, laughing hyenas and humpback whales, respectively. Searching for the prey, encircling and finally attacking it are the basic processes for these optimization algorithms. These algorithms

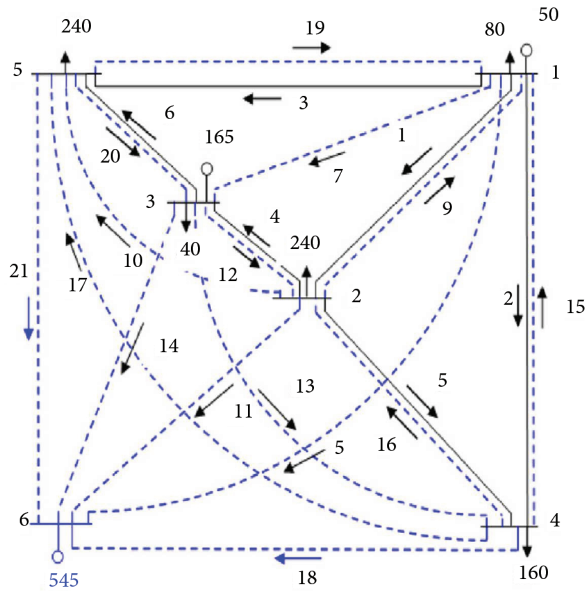


**Figure 1**. Single line diagram of the Garver system.

are based on encircling the prey where the search agents update their positions with respect to the target prey (the best solution). This behavior is mathematically represented as below:

$$\vec{D}_i = \left|\vec{C}\vec{X}_p - \vec{X}_i\right| \tag{10}$$

$$\vec{X}_i = \vec{X}_p - \vec{A}\vec{D}_i \tag{11}$$

where, $A$ and $C$ are co-efficient vectors which are calculated as follows:

$$\vec{A} = 2\vec{a}r - \vec{a} \tag{12}$$

$$\vec{C} = 2r \tag{13}$$

Despite the high resemblance between GWOA, SHOA and WOA in the encircling behavior, they are greatly different in the hunting and attacking operations.

### 3.1.1. Grey wolf optimization algorithm

In GWOA, alpha ($\alpha$) is regarded to be the most dominant participant. Beta ($\beta$) and delta ($\delta$ ) are the remaining subordinates who help regulate the large proportion of wolves regarded by omega $w$. Alpha, beta, and delta have greater awareness of possible locations of preys. Consequently, first ever 3 top members are specified from the whole wolves pack which has a number (Nw) whilst the others in the pack would adjust their locations in the context of the top 3 members. These actions could be expressed in the form (21):

$$\vec{D}_\alpha = \left|\vec{C}_1 - \vec{X}_\alpha - \vec{X}\right| \tag{14}$$

$$\vec{D}_\beta = \left|\vec{C}_1 - \vec{X}_\beta - \vec{X}\right| \tag{15}$$

$$\vec{D}_\delta = \left|\vec{C}_1 - \vec{X}_\delta - \vec{X}\right| \tag{16}$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1 - \vec{D}_\alpha \tag{17}$$

$$\vec{X}_2 = \vec{X}_\beta - \vec{A}_2 - \vec{D}_\beta \tag{18}$$

$$\vec{X}_3 = \vec{X}_\delta - \vec{A}_3 - \vec{D}_\delta \tag{19}$$

$$\vec{X}_{new} = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{20}$$

In GWOA, the co-efficient vector (a) is linearly declined from 2 to 0 through the following equation:

$$\vec{a} = 2 \cdot \left(1 - \frac{iter}{Max_{iter}}\right) \tag{21}$$

### 3.1.2. Spotted hyena optimization algorithm

In SHOA [22], the hunting operation can be described by Eqs. (10) and (11). Then, a cluster of a specified number (N) of optimal solutions (CH) is taken away as follows:

$$\vec{C}_H = \vec{X}_i + \vec{X}_{i+1} + \vec{X}_{i+2} + .....\vec{X}_{i+N} \tag{22}$$

where, N refers to the spotted hyenas umber that is computed as:

$$N = \vec{c}ount_{nos}\left(\vec{X}_i + \vec{X}_{i+1} + \vec{X}_{i+2} + .....\left(\vec{X}_i + \vec{M}\right)\right) \tag{23}$$

where, nos refers to the number of all candidate solutions. M is a randomized vector within the range [0.5, 1]. Afterward, Eq. 24 updates the search agents positions to attack towards the prey as:

$$\vec{X}_{new} = \frac{\vec{C}_H}{N} \tag{24}$$

In SHOA, the co-efficient vector a, which is integrated in Eq. (13), is linearly declined from 5 to 0 through the following equation:

$$\vec{a} = 5 \cdot \left(1 - \frac{iter}{Max_{iter}}\right) \tag{25}$$

### 3.1.3. Whale optimization algorithm

In WOA [23], the whales can update their positions to attack towards the prey via shrinking encircling and the spiral model. Each whale selects one of these two approaches with a probability of 50%. The new positions of the whales can be described as in Eq. (26):

$$X_{new} = \begin{cases} \left(\vec{X}_p - \vec{X}_i\right) \cdot \mathrm{e}^{b1} \cdot \cos(2\pi L) & \text{if } p \geq 0.5. \\ \vec{X}_p - \vec{A} \cdot \left|\vec{C}\vec{X}_p - \vec{X}_i\right| & \text{if } p < 0.5 \text{ and } L > 1. \\ \vec{X}_r - \vec{A} \cdot \left|\vec{C}\vec{X}_r - \vec{X}_i\right| & \text{if } p < 0.5 \text{ and } L \leq 1. \end{cases} \tag{26}$$

where, b is constant. L and p are random number within the ranges [–1, 1] and [0, 1], respectively. $X_r$ refers to a random search agent. Similar to GWOA, the co-efficient vector a, in WOA, is linearly declined from 2 to 0 as in Eq. (21).

### 3.2. Fitness function evaluation

However, the control variables of TNPP is initialized satisfying their bounds. They might be violated during the successive iterations. For this reason, random re-initialization is carried out to modify the violated variable within its consideblack range. In case of the TNPP model considering 100% renewable power penetration, the DC power flow is running each iteration to evaluate the fitness function. On the other side, the DC optimal power flow (OPF) [47] is running to find the most economic operating point and estimate the fitness function. For any violation in the constraints related to the dependent variables, the fitness function is set to a very high level. The three adopted encircling prey based algorithms; GWOA, SHOA and WOA are employed to handle the TNPP. Fig. 2 illustrates the flowchart of their employment.

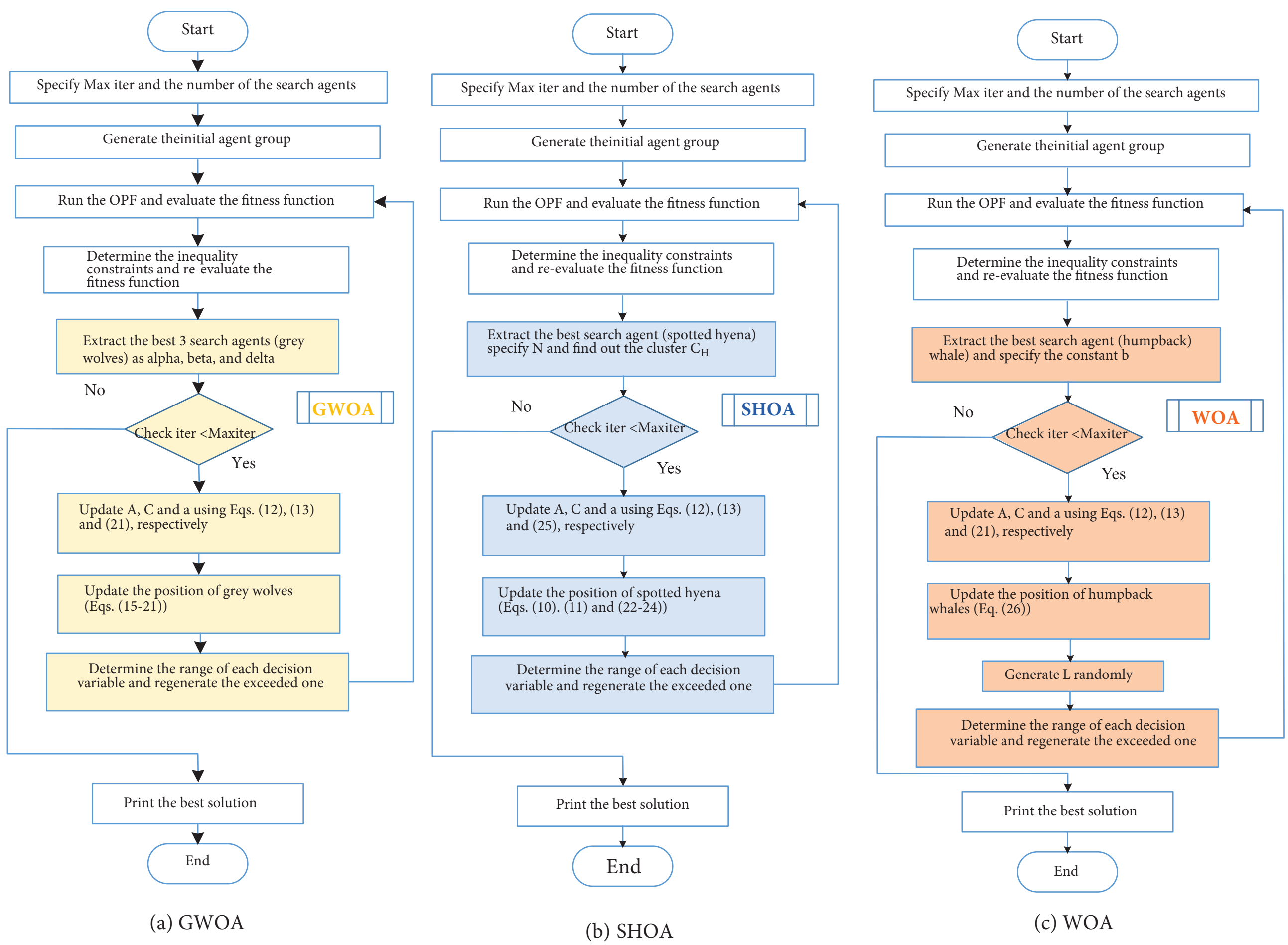


**Figure 2**. The phases of GWOA, SHOA and WOA for the TNPP.

## 4. Applications

### 4.1. Test systems

In this section, the implementation of the three optimization algorithms, GWOA, SHOA and WOA, is carried out using MATLAB (MathWorks, Inc., Natick, MA, USA) on the standard Garver system that is shown in Fig. 1. All the data of this test system is presented in [2]. Then, they are applied for two realistic systems.

The WDR system [48] and [49] and EHV system [50] are two transmission Egyptian networks of 66 and 500 kV, respectively. Figs. 3 and 4 display the one-line diagrams of WDR system and EHV system, respectively. The WDR system has 8-generation stations and 52-buses [52, 53], that are linked via 55 dual circuits. The second system is the EHV system, which consists of 18-buses linked via 19 transmission lines. The data of the generations output, parameters of lines, potential route path and estimated demand forecasting forward to 2030 of both systems are taken from [15]. To search for the optimal configuration parameters of both systems, GWOA, SHOA and WOA is carried out. The maximum iteration number are 300 and 100 for WDR and EHV systems, respectively. The population size is 50 for both systems.

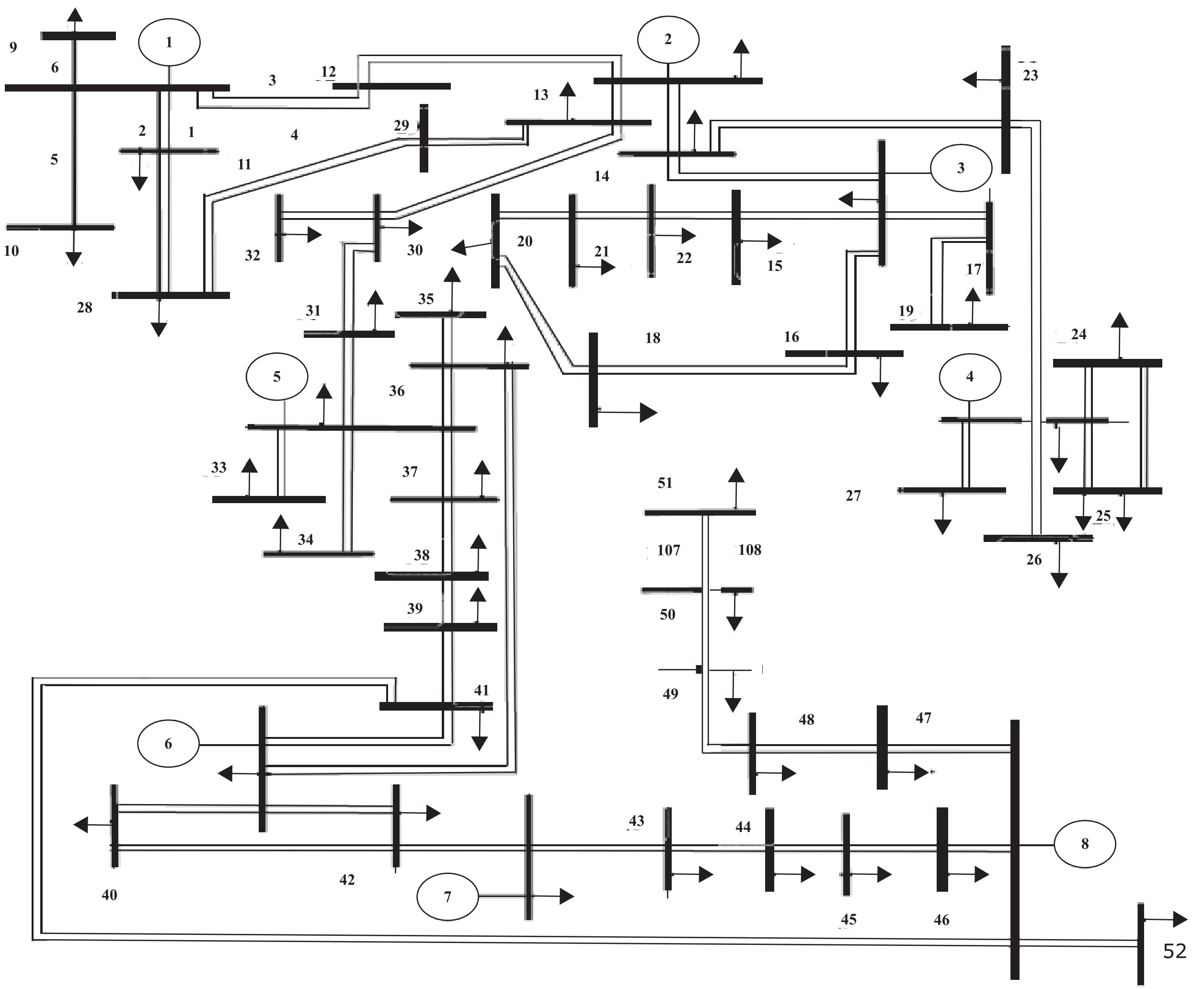


**Figure 3**. SLD of WDR [52].

## 4.2. Simulation results for load forecasting

The ANFIS technique is firstly applied for both systems to expect the load forecasting. Table 1 shows the ANFIS parameter for load forecasting process that is applied for WDN and UEN. Table 2 shows the corresponding results for WDR and EHV systems in the period 2018–2030 based on historical data reported in [17]. For the

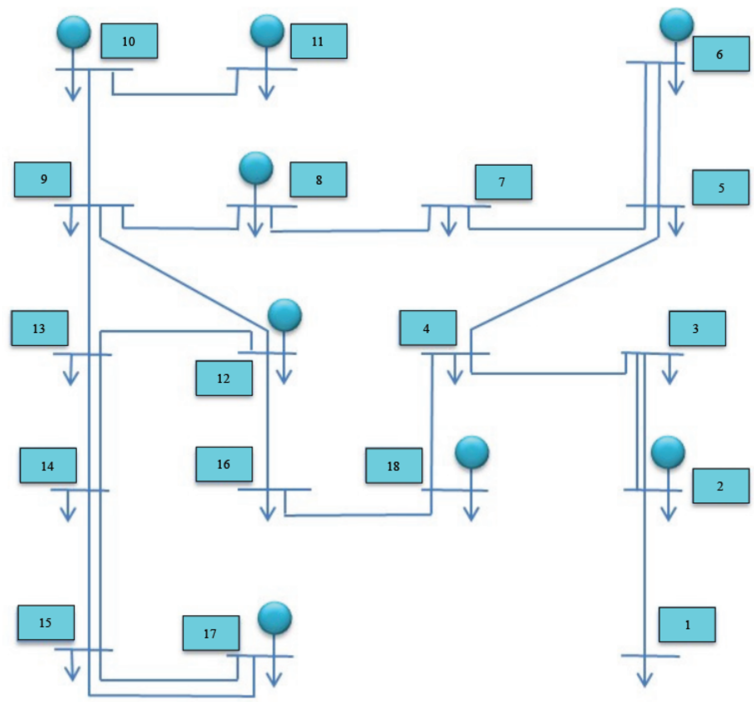


**Figure 4**. SLD for EHV system.

WDR system, it is organized that the load is varied from 1325 MW in 2017 to 2195.8 MW by an excess of 730 MW, which means that there will be a yearly average increase of 5%. For the EHV system, the load is expected to increase from 9240.55 MW in 2017 to around 13176.9 MW. The evaluation test for ANFIS results is reported in Table 3. The obtained results are very competitive and acceptable in the viewpoint of load forecasting process.

**Table 1**. ANFIS parameters for tested systems.

| **Number of parameters** | **WDR system** | **EHV system** |
|---|---|---|
| Nodes | 16 | 64 |
| Fuzzy rules | 3 | 15 |
| Training pairs of data | 7 | 23 |
| Checking pairs of data | 1 | 1 |
| Linear parameters | 6 | 30 |
| Nonlinear parameters | 9 | 45 |

### 4.3. Standard Garver system

In this system, it is planned to face expected demand of 760 MW. Table 4 presents the new configuration of Garver 6-bus network using the GWOA compablack with IBPSO [2] and HT [9]. For the first model, the findings obtained from GWOA are similar to those of IBPSO [2] and HT [9]. All approaches have 13 directions with a cost of $200 million. On the other hand, in the planned Model 2, the GWOA gains substantial advantages

**Table 2**. Forecasting loads for WDRS and EHVS using ANFIS.

| Year | WDRS Loads (MW) | EHVS Loads (MW) |
|---|---|---|
| 2016 | 1260.18 | 9112.06 |
| 2017 | 1325 | 9345.07 |
| 2018 | 1390.56 | 9481.86 |
| 2019 | 1456.57 | 9631.38 |
| 2020 | 1522.98 | 9822.35 |
| : | : | : |
| 2027 | 1993.24 | 12010.36 |
| 2028 | 2060.73 | 12390.52 |
| 2029 | 2128.26 | 12779.86 |
| 2030 (Target year) | 2195.80 | 13176.90 |

**Table 3**. Evaluation criteria for the tested networks.

| Number of parameters | WDR system | EHV system |
|---|---|---|
| Test | WDR | EHV |
| R2 | 0.9961697 | 0.9999992 |
| E | 47.3 | 2 |
| D.W | 3.6282 | 3 |
| MAE | 5.912 | 0.087 |
| MAE/E% | 12.87 | 4.35 |
| % MAPE | 0.625717624 | 0.00033 |

when it identifies an economic operating point with a fuel cost of $10540.17 per hour with a decrease of 6.74 % relative to a fuel cost of $11301.7905 per hour for model 1. However, it substantially decreases the construction costs of the new installed lines, which cost $130 million, with a decrease of 35% relative to the investment cost of $200 million for the model 1. These benefits declare the capability of the model 2 in minimizing the investment costs of the new installed lines to the system besides finding an economic operating point.

### 4.4. West delta region system

In this system, it is expected to face the projected peak demand of 2195.8 MW whilst a new generator station is designed to be installed at bus 53 where 31 additional routes are possible to be constructed.

#### 4.4.1. Simulation results of model 1

In this model, the decision vector contains only the possible new lines to be constructed. Therefore, 31 dimensional variables in the decision vector are designed to minimize the costs of investment for the regarded additional circuits. The encircling prey-based algorithms are adopted for solving the TNPP in the WDR system, and the concerning outputs are staggeblack in Table 5. The minimum investment cost of 18.105 US million $ is achieved through the application of the GWOA that detected the new routs (57/1; 63/1; 77/1; 80/1; 81/2; 84/2) with 362.1 km for the corresponding length of these added lines for WDR system. Following to this,

**Table 4**. Application of the GWOA for Garver system for models 1 and 2

| Item | Model 1 | | | | | Model 2 | | |
|---|---|---|---|---|---|---|---|---|
| | HT [9] | IBPSO [2] | SHOA | GWOA | WOA | SHOA | GWOA | WOA |
| Terminal From-to (line number)/ circuits number | 1-3(7)/1 | 1-3(7)/1 | 1-3(7)/1 | 1-3(7)/1 | 1-3(7)/1 | 1-4(8)/1 | 1-3(7)/1 | 1-4(8)/1 |
| | 1-2(9)/1 | 1-2(9)/1 | 1-2(9)/1 | 1-2(9)/1 | 1-2(9)/1 | 1-2(9)/1 | 1-2(9)/1 | 1-2(9)/1 |
| | 2-5(10)/1 | 2-5(10)/1 | 2-5(10)/1 | 2-5(10)/1 | 2-5(10)/1 | 1-5(11)/1 | 2-5(10)/1 | 1-5(11)/1 |
| | 3-4(12)/1 | 3-4(12)/1 | 3-4(12)/1 | 3-4(12)/1 | 3-4(12)/1 | 2-4(14)/1 | 3-4(12)/1 | 2-4(14)/1 |
| | 3-6(13)/1 | 3-6(13)/1 | 3-6(13)/1 | 3-6(13)/1 | 3-6(13)/1 | 2-3(16)/1 | 3-6(13)/1 | 2-3(16)/1 |
| | 1-4(15)/4 | 1-4(15)/4 | 1-4(15)/4 | 1-4(15)/4 | 1-4(15)/4 | 2-6(18)/3 | 1-4(15)/1 | 2-6(18)/3 |
| | 4-5(17)/2 | 4-5(17)/2 | 4-5(17)/2 | 4-5(17)/2 | 4-5(17)/2 | 3-4(19)/1 | 4-5(17)/2 | 3-5(20)/3 |
| | 3-5(20)/3 | 3-5(20)/3 | 3-5(20)/2 | 3-5(20)/2 | 3-5(20)/2 | 3-5(20)/2 | 3-5(20)/2 | 3-5(20)/3 |
| Pg1 (MW) | 50 | 50 | 50 | 50 | 50 | 150 | 150 | 150 |
| Pg2 (MW) | 165 | 165 | 165 | 165 | 165 | 310 | 346.54 | 310 |
| Pg3 (MW) | 545 | 545 | 545 | 545 | 545 | 300 | 263.46 | 300 |
| Fuel cost ($/hr) | 11301.7905 | 11301.7905 | 11301.7905 | 11301.7905 | 11301.7905 | 10497.73 | 10540.17 | 10497.73 |
| Total costs (Millions $) | 200 | 200 | 200 | 200 | 200 | 189 | 130 | 130 |

the WOA achieves as investment costs of 18.805 US million $ while the SHOA achieves the highest cost of 20.905 US million $. Also, these acquired results via the GWOA, SHOA and WOA are matched with other reported results for HT [9], IBPSO [15], MVO [16], IBSO [17] and BBSO [17] as demonstrated in Table 4 while Figure 5 depicts the convergence characteristics of MVO [16], IBSO [17], BBSO [17] and the encircling prey based algorithms. From the comparison in Table 6 and Fig. 5, the GWOA outperforms the other techniques in solving the TNPP. Fig. 5 shows a higher capability of the GWOA over SHOA and WOA in exploring the search space and improving their best search agent through the iterations.

**Table 5**. Application of the encircling prey based algorithms for WDR system for model 1.

| | **GWOA** | **SHOA** | **WOA** |
|---|---|---|---|
| Terminal From-to (line number)/ circuits number | 5-7(57)/1 | 5-6(56)/1 | 6-34(63)/1 |
| | 6-34(63)/1 | 5-22(59)/1 | 7-37(69)/1 |
| | 22-53(77)/1 | 6-34(63)/1 | 22-53(77)/1 |
| | 33-53(80)/1 | 7-32(65)/1 | 33-53(80)/1 |
| | 5-53(81)/2 | 31-53(80)/1 | 5-53(81)/2 |
| | 36-53(84)/2 | 5-53(81)/2 | 36-53(84)/2 |
| | | 36-53(84)/2 | |
| | | 20-53(85)/1 | |
| Length (km) | 362.1 | 418.1 | 376.1 |
| Total costs (Millions $) | 18.105 | 20.905 | 18.805 |

#### 4.4.2. Simulation results of model 2

In this model, the minimization of the fuel cost related to the generated power is augmented with minimizing the added circuits investment costs. Subsequently, the decision vector to be optimized is expounded by the output

**Table 6**. Comparison of the simulation results for WDR system using different optimization algorithms.

| **Method** | **Length (km)** | **Total costs (millions $)** |
|---|---|---|
| IBPSO [15] | 443.8 | 22.19 |
| HT [9] | 424.8 | 21.24 |
| SHOA | 418.1 | 20.905 |
| MVO [16] | 412.9 | 20.645 |
| WOA | 376.1 | 18.805 |
| IBSO [17] | 372.1 | 18.605 |
| BBSO [17] | 369.1 | 18.455 |
| GWOA | 362.1 | 18.105 |

power from 9 generators besides 31 candidate new lines. The encircling prey-based algorithms are applied 10 times to handle this model for the WDRS associated with their best simulation records are staggeblack in Table 7.

The minimum investment costs of 7.72 US million $ that are acquired through the application of GWOA and WOA that detected the new routs (59/1; 80/1; 84/1) with 154.4 km for the corresponding length of these added lines for WDRS. The SHOA cannot achieve a competitive result since their best value of 10.07 US million $ is bigger than GWOA and WOA. In comparison of both TNP models, the GWOA application for model 2 achieves great benefits. It finds out an economic operating point with fuel costs of 64688 $/hr with blackuction of 6.44 % compablack to fuel costs of 69140 $/hr for model 1. Nevertheless, it greatly blackuces the investment costs of the new installed lines which costs 7.72 US million $ with blackuction of 57.36 % compablack to the investment costs of 18.105 US million $ for model 1. These merits assert the ability of the model 2 for minimizing the new installed transmission lines investment costs to the system besides finding an economic operating point. Fig. 6 displays the investment costs that are obtained using GWOA, SHOA, WOA, MVO and IBSO after 10 individual runs to handle the second model (Model 2) for the WDRS. The concerning results are in an ascending order. This figure demonstrates the out-performance of the GWOA over the others since it acquires mostly lower investment costs of the lines. Their statistical indexes are tabulated in Table 8. This table shows the capability of the GWOA in solving TNPP by acquiring mostly the minimum objective of best, average and worst indexes of 7.72, 8.215 and 10.195, respectively compared with the others. The SHOA gives minimum standard deviation and error of 0.553 and 0.175, respectively. Despite SHOA's higher stability, their best index doesn't exceed the average value related to the GWOA.

### 4.5. Extra high voltage system

#### 4.5.1. Simulation results of model 1

In this system, it is expected to face the projected peak demand of 13176.90 MW at 2030 as shown in Table 2. For the first model, the investment costs are considerable as the primary objective function. For this target, 19 dimensional variables in each decision vector are optimized. The GWOA, SHOA and WOA are operated to solve this model for 10 individual runs and the best concerning results are reported in Table 9. GWOA, SHOA and WOA are successfully gaining the minimum investment costs of 279 US million $ where the new routes are (36/1; 37/1). In addition, these achieved results via the encircling prey based algorithms are matched with other reported results for IBPSO [15], MVO [16], IBSO [17] and BBSO [17] as demonstrated in Table 10.

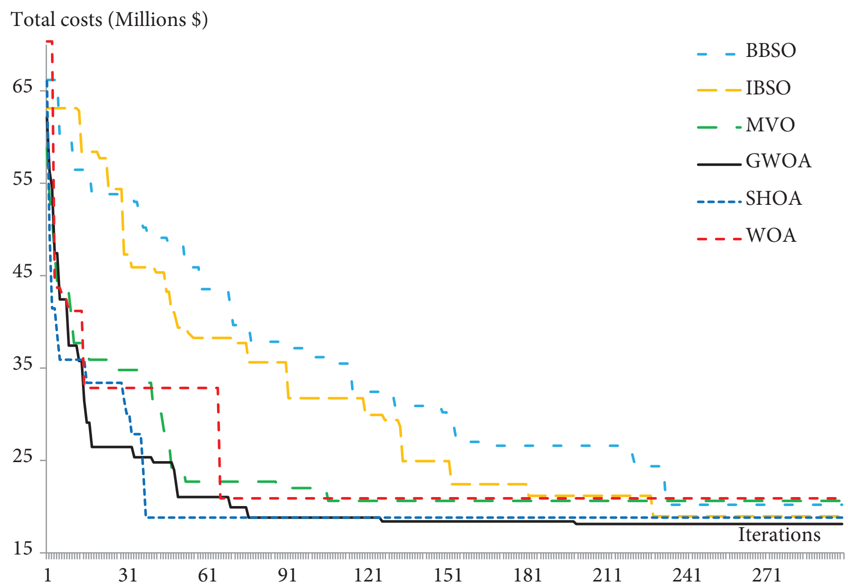


**Figure 5**. Convergence rate of MVO, IBSO, BBSO and the competitive algorithms for WDR system (model 1).

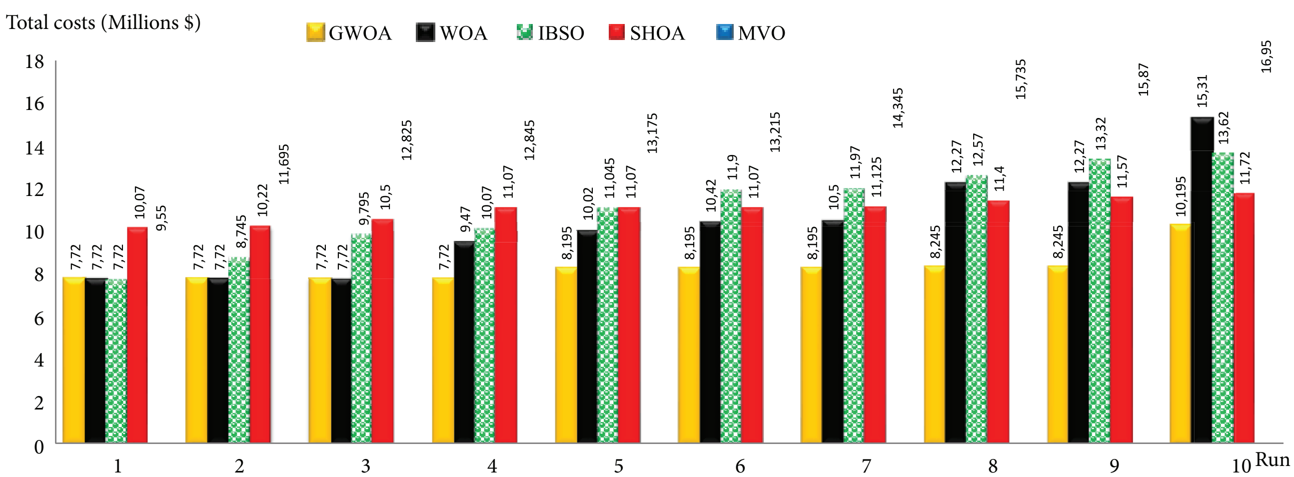


**Figure 6**. Acquired investment costs (Millions $) of MVO, IBSO and the competitive algorithms for WDRS (TNP model 2).

This table illustrates the outperforms of the encircling prey-based algorithms over the other reported techniques of the new installed lines, which cost 25 US million $ compablack to the investment cost of 279 US million $ for TNP model 1. These benefits declare the capability of the proposed TNP model 2 in minimizing the investment costs of the new installed lines to the system besides finding an economic operating point.

### 4.5.2. Simulation results model 2

In the second model, the TNPP considers an improved objective function that combines the costs investment and operating costs at the target planning year. So, 27 decision variables (the output power from 8 generation stations besides 19 candidate new lines), are involved in the decision vector to be optimized. The encircling

**Table 7**. Application of the encircling prey based algorithms for WDR system(model 2).

| Item | Model 1 | | | Model 2 | | |
|---|---|---|---|---|---|---|
| | GWOA | SHOA | WOA | GWOA | SHOA | WOA |
| Terminal From-to (line number)/ circuits number | 5-7(57)/1 | 5-6(56)/1 | 6-34(63)/1 | 5-22(59)/1 | 5-22(59)/1 | 5-22(59)/1 |
| | 6-34(63)/1 | 5-22(59)/1 | 7-37(69)/1 | 31-53(80)/1 | 31-53(80)/1 | 31-53(80)/1 |
| | 22-53(77)/1 | 6-34(63)/1 | 22-53(77)/1 | 36-53(84)/2 | 8-53(86)/1 | 36-53(84)/2 |
| | 33-53(80)/1 | 7-32(65)/1 | 33-53(80)/1 | | | |
| | 5-53(81)/2 | 31-53(80)/1 | 5-53(81)/2 | | | |
| | 36-53(84)/2 | 5-53(81)/2 | 36-53(84)/2 | | | |
| | | 36-53(84)/2 | | | | |
| | | 20-53(85)/1 | | | | |
| Pg1 (MW) | 200 | 200 | 200 | 250* | 250* | 250* |
| Pg2 (MW) | 200 | 200 | 200 | 134.981 | 131.338 | 131.338 |
| Pg3 (MW) | 200 | 200 | 200 | 250* | 250* | 250* |
| Pg4 (MW) | 156 | 156 | 156 | 250* | 250* | 250* |
| Pg5 (MW) | 300 | 300 | 300 | 254.5607 | 219.1787 | 205.9214 |
| Pg6 (MW) | 100 | 100 | 100 | 250* | 250* | 250* |
| Pg7 (MW) | 200 | 200 | 200 | 250* | 250* | 250* |
| Pg8 (MW) | 200 | 200 | 200 | 250* | 250* | 250* |
| Pg53 (MW) | 639.8 | 639.8 | 639.8 | 306.2584 | 345.2832 | 358.5406 |
| Fuel cost ($/hr) | 69140.012 | 69140.012 | 69140.012 | 64688 | 64751.64 | 64769.66 |
| Length (km) | 362.1 | 418.1 | 376.1 | 154.4 | 201.4 | 154.4 |
| Total costs (Millions $) | 18.105 | 20.905 | 18.805 | 7.72 | 10.07 | 7.72 |

[*] refers to strike the maximum limit.

**Table 8**. Statistics of the investment costs (millions $) of the GWOA, SHOA, WOA, MVO and IBSO for WDR (Model 2).

| | **MVO** | **IBSO** | **GWOA** | **SHOA** | **WOA** |
|---|---|---|---|---|---|
| Best | 9.55 | 7.72 | 7.72 | 10.07 | 7.72 |
| Average | 13.62 | 11.07 | 8.215 | 10.9815 | 10.342 |
| Worst | 16.95 | 13.62 | 10.195 | 11.72 | 15.31 |
| St. deviation | 2.186 | 1.959 | 0.7381 | 0.5531 | 2.4412 |
| St. error | 0.691 | 0.619 | 0.2334 | 0.175 | 0.772 |

prey based algorithms are applied 10 times to handle this model for the WDR system, and their best results are shown in Table 9. As shown, the minimum investment costs of 25 US million $ is acquired through the application of GWOA that installed two single transmission lines (7–8 (31) and 8–9 (32)) while SHOA and WOA achieve an investment costs of 32 US million $. In comparison of both TNP models, the application of the GWOA for TNP model 2 achieves great benefits in minimizing the fuel costs of 522751.94 $/h with blackuction of 19.17 % compablack to fuel costs of 646707.898 $/h for TNP model 1. Nevertheless, it greatly blackuces the investment costs.

**Table 9**. Application of the encircling prey based algorithms for EHV system for the models 1 and 2.

<table>
<tr><td rowspan="2">Variable</td><td colspan="3">Model 1</td><td colspan="3">Model 2</td></tr>
<tr><td>GWOA</td><td>SHOA</td><td>WOA</td><td>GWOA</td><td>SHOA</td><td>WOA</td></tr>
<tr><td rowspan="2">From-to line/no. of routes</td><td>9–12 (36)/1</td><td>9–12 (36)/1</td><td>9-12 (36)/1</td><td>7–8 (31)/1</td><td rowspan="2">8-9 (32)/2</td><td rowspan="2">8-9 (32)/2</td></tr>
<tr><td>13–12 (37)/1</td><td>13–12 (37)/1</td><td>13–12 (37)/1</td><td>8–9 (32)/1</td></tr>
<tr><td>Pg2 (MW)</td><td>5091. 89</td><td>5091. 89</td><td>5091. 89</td><td>1446.86</td><td>1445.19</td><td>1445.19</td></tr>
<tr><td>Pg6 (MW)</td><td>570</td><td>570</td><td>570</td><td>2094.47</td><td>2089.42</td><td>2089.42</td></tr>
<tr><td>Pg8 (MW)</td><td>1200</td><td>1200</td><td>1200</td><td>2500*</td><td>2500*</td><td>2500*</td></tr>
<tr><td>Pg10 (MW)</td><td>1057</td><td>1057</td><td>1057</td><td>1469.23</td><td>1469.23</td><td>1469.23</td></tr>
<tr><td>Pg11 (MW)</td><td>1839</td><td>1839</td><td>1839</td><td>1897.36</td><td>1897.36</td><td>1897.36</td></tr>
<tr><td>Pg12 (MW)</td><td>719</td><td>719</td><td>719</td><td>905.9</td><td>910.97</td><td>910.97</td></tr>
<tr><td>Pg17 (MW)</td><td>2020</td><td>2020</td><td>2020</td><td>2500*</td><td>2500*</td><td>2500*</td></tr>
<tr><td>Pg18 (MW)</td><td>680</td><td>680</td><td>680</td><td>363.08</td><td>364.74</td><td>364.74</td></tr>
<tr><td>Fuel cost ($/hr)</td><td>646707.9</td><td>646707.9</td><td>646707.9</td><td>522751.9</td><td>522689.8</td><td>522689.8</td></tr>
<tr><td>Total costs (Millions$)</td><td>279</td><td>279</td><td>279</td><td>25</td><td>32</td><td>32</td></tr>
</table>

[*] Refers to strike the maximum limit.

**Table 10**. Assessment of simulation results for WDRS using different optimization algorithms.

| **Method** | **Total costs (millions $)** |
|---|---|
| GWOA | 279 |
| WOA | 279 |
| SHOA | 279 |
| BBSO [15] | 288 |
| IBSO [17] | 288 |
| MVO [16] | 295 |
| IBPSO [15] | 308 |

#### 4.5.3. Statistical analysis

The statistical indices of the encircling prey based algorithms are tabulated in Table 11. This table shows the capability of the GWOA in acquiring mostly the minimum objective of best, average and worst indices of 279 and 25 US million $ for models 1 and 2, respectively. Not only that, but it has the greatest stability with zero standard deviation and error for both models as well. The worst value of investment costs that obtained by the WOA is the highest compablack than the best one related to SHOA and GWOA. For more clearance, Fig. 7 shows the convergence rate the competitive algorithms for EHV system (model 2). Also, Fig. 8 shows the acquired investment costs (millions $) of the competitive algorithms for EHV system (TNP model 2). From Table 11 and Figs. 7 and 8, it is clear that the GWOA has the best convergence rates and robustness compablack with other two algorithms.

#### 4.5.4. Validity of the EHV configurations

Based on previous sections, it was proven that GWOA has the best performance compablack with SHOA and WOA methods. In this subsection, the validity is carried out by using the best optimization algorithm only as

**Table 11**. Statistics of the investment costs (millions $) of the GWOA, SHOA, WOA for EHV system.

| Model | Statistical indices | WOA | SHOA | GWOA |
|---|---|---|---|---|
| Model 1 | Best | 279 | 279 | 279 |
| | Average | 290.6 | 287.8 | 279 |
| | Worst | 308 | 308 | 279 |
| | St. deviation | 4.7357 | 4.429823 | 0 |
| | St. error | 14.9755 | 14.00833 | 0 |
| Model 2 | Best | 32 | 32 | 25 |
| | Average | 112.86 | 32 | 25 |
| | Worst | 424.6 | 32 | 25 |
| | St. deviation | 43.4612 | 0 | 0 |
| | St. error | 137.43 | 0 | 0 |

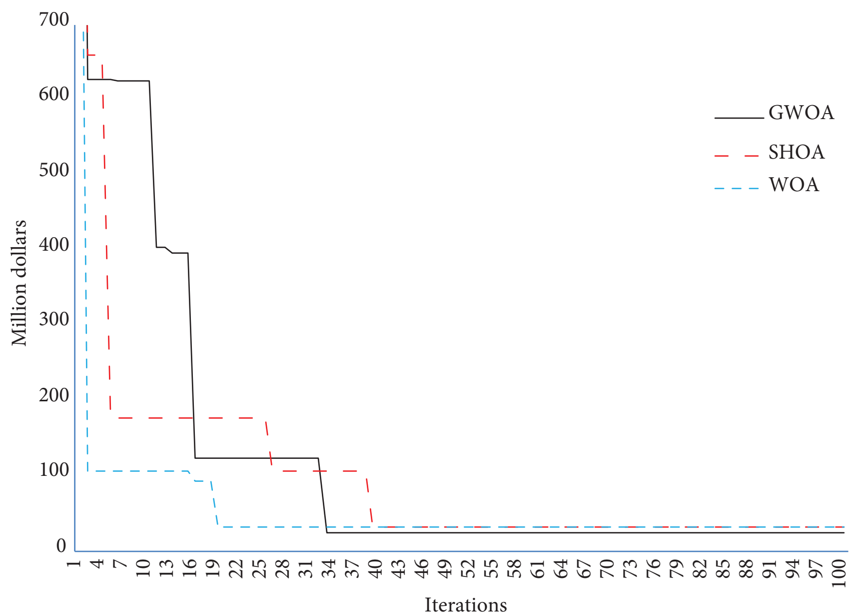


**Figure 7**. Convergence rate the competitive algorithms for EHV system (model 2).

the recommended one for this study. Fig. 9 displays the power flow in the EHV system for the output results using the GWOA to face the expected demand at 2030 for both models. This figure illustrates the validity of the configuration using the GWOA since all the flows are within its limits.

## 5. Conclusion

This paper proposes a developed model of the TNPP by searching for the most economic operating point via dispatching the generators output besides finding the minimum cost of new transmission line to the system. In addition to that, three recent algorithms of GWOA, SHOA and WOA have been employed to solve the TNPP. They have been applied to two realistic Egyptian networks of the WDR and the EHV systems. Their pblackicted load forecasting has been extracted up to 2030 based on ANFIS. The out-performance of the GWOA has been

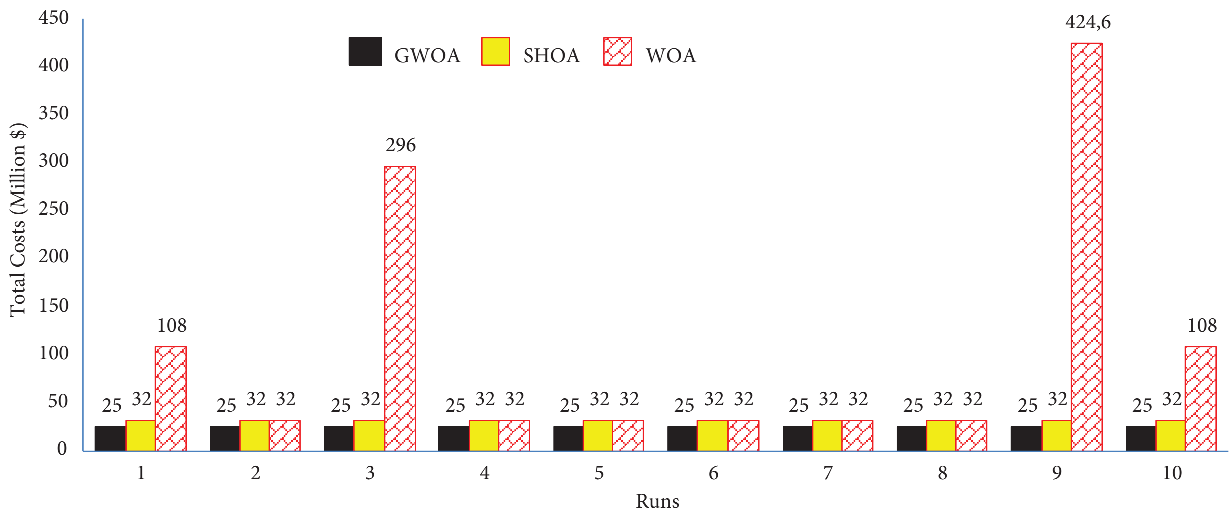


**Figure 8**. Investment costs (millions $) of the competitive algorithms for EHV system (TNP model 2).

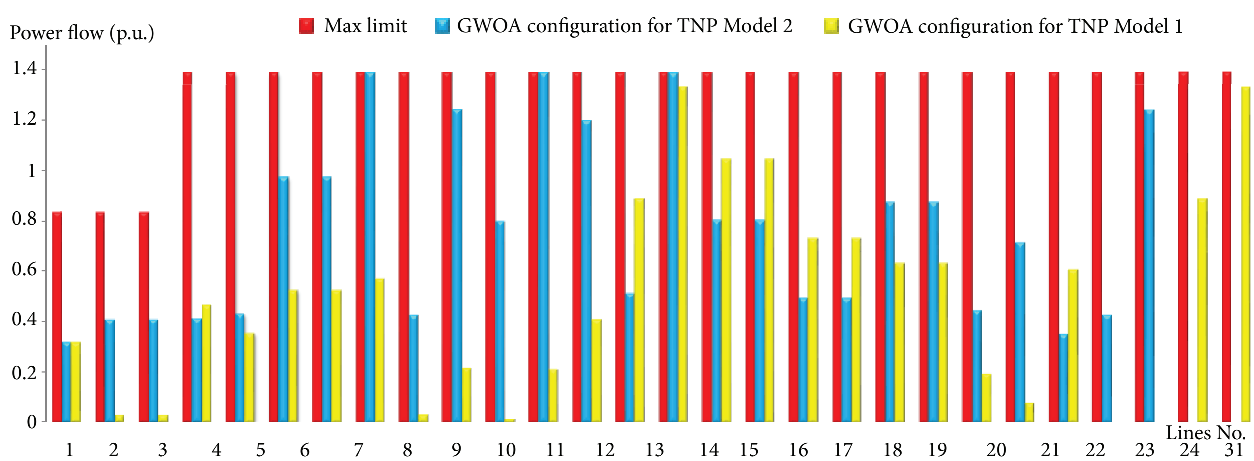


**Figure 9**. Power flow related to the output results using the GWOA for EHV system.

appeablack in minimizing the installation costs of the new lines and minimizing the fuel costs since it achieved the minimum value compablack to HT, IBPSO, MVO, IBSO, BBSO, SHOA and WOA for the conventional and developed TNP models. In addition, a higher capability of the GWOA has been demonstrated over SHOA and WOA in exploring the search space and improving their best search agent through the iterations. Also, the statistical analysis declares the high stability of the GWOA in acquiring mostly the minimum objective with zero standard deviation and error for EHV system. Moreover, the validity of the configurations using the GWOA has been verified since all the MW flows are within its limits. On another direction, great benefits in minimizing the investment costs of the new installed lines besides blackucing the fuel costs have been achieved via the application of the GWOA for the developed model of the TNPP. Extension of this paper can be carried by considering the existence of renewable energy resources considering their environmental conditions. Also, applying new hybrid AC/DC grids as new models in the TNEP. Also, developing new optimization methods are welcome such as sunflower, equilibrium, mant ray optimization algorithms.

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