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RESEARCH ARTICLE

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TRANSMISSION NETWORK EXPANSION STATIC PLANNING CONSIDERING SECURITY CONSTRAINTS VIA AFRICAN BUFFALO ALGORITHM

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ABSTRACT

In this paper, the African Buffalo Optimization (ABO) is adapted to solve the transmission network expansion static planning problem considering security restrictions (TNESPS). The problem is formulated as a mixed-integer nonlinear programming (MINLP) problem. The ABO is based on the collective intelligence of the African buffaloes searching for food in the savannahs. The proposed algorithm uses the direct current model to represent the network, the transport model to generate the initial population, and two candidate solution improvement procedures, one being cost reduction and the other feasibility of infeasible solutions. The analysis of the specialized literature shows that the proposed algorithm has never been used to solve the static or dynamic TNESP problem, with or without security restrictions. Thus, this paper contributes to a new methodological approach to solving TNESPS problems. To evaluate the performance of the proposed algorithm, three systems that are often used in evaluations of new methodologies were used: Garver 6-bus system, IEEE 24-bus system and the South Brazilian 46-bus system.

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I. INTRODUCTION

In a power electric system, the transmission grid is responsible for transporting the energy produced in the electric power generation centers to the large consumption centers. Determining the grid that adequately meets future demand at the lowest possible investment cost is a very complex long-term expansion planning task, as it involves the need to consider, simultaneously, aspects related to: the location of future energy generation and consumption centers, the grid size and topology, the adoption or not of security criteria (N-0 or N-1 criteria), the costs and electrical parameters of circuits (existing and candidate), the candidate circuits, the system modeling (alternating current - AC or direct current - DC) [1] and the number of planning periods (static and dynamic planning), the uncertainties and the solution method.

In static planning [2], it only determines where and how many circuits from the candidate list should be added to the initial configuration. In dynamic planning [3], where several horizon periods are considered, it is also determined when the new circuits should be added.

This work addresses the of transmission network expansion static planning problem considering security constraints (TNESPS). These types of constraints guarantee that future demand will be met even in the event of a simple contingency in any of the circuits of the transmission grid.

This problem presents great mathematical complexity due to the following particularities [4], [5]: (a) has integer and continuous variables, i.e., it is a mixed integer nonlinear programming (MINLP) problem; (b) non-convex search space, causing several types of algorithms to prematurely converge to local optimal solutions; (c) presents the combinatorial explosion phenomenon, causing the amount of candidate solutions to be analyzed to grow exponentially as a function of the system size; (d) requires high computational effort to find the global optimal solution or to find a high quality solution; (e) contains isolated bus.

Currently, there is a wide variety of solving techniques that can cope with the above-mentioned particularities. In the bibliography they are grouped according to the types of algorithms used [4-9]: (i) classical optimization algorithms, (ii) constructive heuristic algorithms and (iii) metaheuristic algorithms.

Algorithms based on classical optimization explore the entire search space and are guided by the gradients of the objective function to move through the search space to find the optimal solution. They usually find the global optimal solution for small systems. However, for large systems, they present problems related to processing time and convergence. Therefore, these algorithms often become unsuitable for solving TNESPS [10]. With these characteristics, TNESPS can be considered an NP-complete type problem [3], that is, there is no method that can solve it in polynomial time.

Constructive heuristic algorithms use simplified procedures that have the ability to identify good quality solutions for small to medium-sized systems with little computational effort. They rarely find the global optimum solution to the problem.

Metaheuristic algorithms use much more elaborate search procedures, usually based on phenomena in nature, to explore the search space and escape from local optimum solutions. For this reason, metaheuristic algorithms frequently obtain solutions of higher quality than the quality of solutions obtained with heuristic algorithms. Moreover, they often find high quality solutions and even the optimal solution with acceptable computational effort, even in large systems [11].

One of the main advantages of metaheuristic algorithms over the other two algorithms is that they generally require little or no information from the TNESPS problem to guide the search process, i.e., they require few adjustments to their parameters [12].

The advantages cited, along with the good compromise ratio (quality of the final solution/computational effort), has caused the amount of research performed with metaheuristic algorithms to grow in the last decades, as shown in the list of published articles described below.

In all the papers in this list, the DC load flow model was used to represent the transmission network. The systems used to test the various proposed algorithms were as follows: Garver-6 bus/15 branches (G-6/15), IEEE-24 bus/41 branches (IEEE-24/41), South Brazilian-46 bus/79 branches (SB-46/79), Colombian-93 bus/155 branches, East Chinese reduced from 18 bus/27 branches and the Brazilian-242 bus/467 branches.

This growth demonstrates the great importance that the TNESPS problem has for researchers and the need to develop algorithms capable of offering a balance in terms of the final quality of the solutions and the computational cost.

As can be observed, the application of the metaheuristic algorithm African Buffalo Optimization - ABO [13], [14] to solve the planning problem, both in the static and dynamic versions, with or without safety constraints, is not included in the list of published articles. This novelty, coupled with the fact that the discussion of the TNESPS subject is still open, was what motivated this work.

The proposed metaheuristic algorithm, named ABO_{N-1} optimizer uses the concepts of the ABO algorithm, along with the two local improvement strategies used by Chu-Beasley (CB) [15], successfully used by Silva et al. [16], to solve the TNESPS problem. One of the strategies seeks to reduce the cost of feasible solutions by removing added circuits that are redundant. The other strategy seeks to enable candidate solutions with load shedding, by adding new circuits. The joint application of these two strategies is very important when the system is large.

In the ABO_{N-1} optimizer, the TNESPS is formulated as a mixed-integer nonlinear programming (MINLP) problem, using the DC model to determine the power flows in the transmission network circuits. The transportation model [17] is used to help generate the initial population.

Updates and improvements to the initial population solutions are made over iterations following the equations and rules established by the ABO algorithm. The other population solutions are generated through random variations in the circuits of the first solution. Throughout the iterations, the initial population solutions are updated according to the equations and rules established by the ABO algorithm, and Chu-Beasley's local improvement strategies.

Aiming to contribute with another solving method to the TNESPS problem, this paper is organized as follows: Section III describes the mathematical model that was used in the problem. Section IV presents the solving method that was used to solve the problem. Section V presents and discusses the results that were obtained by the proposed method in three case studies performed with the G-6/15, IEEE-24/41 and SB-46/79 systems. Section VI presents the main conclusions.

- ***List of Articles***

Silva et al., 2005 [2] - Chu-Beasley Genetic Algorithm (CBGA); Gallego et al., 2006 [18] - CBGA; Jin et al., 2007 [19] - Particle Swarm Optimization (PSO) based on Model Space Theory; Yemula et al., 2008 [20] - Z-bus Based Genetic Algorithm; Verma et al., 2008 [21], [22] - Binary Genetic Algorithm; Gang et al., 2008 [23] - Chaos Optimization Algorithm; Verma et al. 2009 [24] - Adaptive PSO Algorithm; Fan et al., 2009 [25] - Niching Genetic Algorithm; Limsakul et al. 2009 [26] - Ant Colony Optimization; Verma et al. 2010 [27] - Harmony Search Algorithm (HSA); Verma et al., 2010 [28] - Bacteria Foraging and Differential Evolution; Orfanos et al. 2012 [29] - Improved HSA; Shivaie et al., 2013 [30] - Improved HSA; Sarrafan 2014 [31] - Discrete Parallel Particle Swarm Optimization; Correa et al., 2014 [32] - Non-dominated Sorting Genetic Algorithm; Das et al. 2017 [33] - Artificial Bee Colony (ABC); Da Silva et al. 2016 [34] - Adaptive Multi-Operator Evolutionary Algorithm; Da Silva et al., 2017 [35] - Constructive Heuristic and Evolutionary Metaheuristic; Khandelwal et al. 2019 [36] - Grey Wolf Optimization; Nepomuceno et al., 2020 [37] - Spotted Hyena Optimization; Fernando et al., 2020 [38] - Constructive Metaheuristic Algorithm.

II. MATHEMATICAL MODEL OF THE PROBLEM

The objective of the TNESPS problem is to define the least-cost set of circuits that must be added to the base transmission network in order to meet the total expected load in the event of any simple contingency.

II.1 OBJECTIVE FUNCION OF THE PROBLEM

The objective function used by the ABO_{N-1} optimizer is composed of two terms, as in [2]: the first term evaluates the total cost of investments in new circuits and the second evaluates the load shedding with the network intact and in simple contingency. The second term is necessary in cases where the proposed solution is not able to meet the expected load without violating the transmission capacities of the circuits. The ABO_{N-1} optimizer determines, at each iteration, the set of the least cost circuits such that the second term is zero.

$$Min\ v = \{\textstyle\sum_{(i,j)\in\Omega_r} c_{ij} n_{ij} + \alpha \sum_{(b\in\Omega_b)} (r_b^n + r_b^p)\} \qquad (1)$$

In this function, c_{ij} is the cost of the circuit added on branch ij; n_{ij}- number of circuits added on branch ij; r_b^n, r_b^p- load shedding at bus $b \in \Omega_b$, with the network operating with all network circuits and without circuit $p \in$ Lc, respectively; Lc- contingency list; Ω_b- set of load bars; Ω_r- set of network branches; α- unit transformation parameter.

II.2 EQUALITY CONSTRAINTS

In the ABO_{N-1} optimizer, the transmission network is represented by the DC load flow model [1], [2], since it calculates the power flows in the circuits very quickly and accurately compatible with the long-term planning horizon. In this simplified model only the active loads and generations, and the angles of the voltages at the bars are represented. With this simplification, the equality constraints used in TNESPS modeling are represented by equations (2) and (3), adapted from [2]. The parameters β and δ were introduced in order to compact the model.

$$(1-\delta)(Sf^n + g^n + r^n) + \delta(Sf^p + g^p + r^p) = d \qquad (2)$$

$$(1-\beta)(1-\delta)\left[f_{ij}^n - \gamma_{ij}\left(n_{ij}^0 + n_{ij}\right)\left(\theta_i^n - \theta_j^n\right)\right] + \delta\left[f_{ij}^p - \gamma_{ij}\left(n_{ij}^0 + n_{ij} - \beta\right)\left(\theta_i^p - \theta_j^p\right)\right] = 0 \qquad (3)$$

The two sets of linear constraints (2), one for δ=0 and the other for δ=1, model, respectively, the energy conservation at each bar of the system, for a network operating without and with simple contingency. That is, set (2) models Kirchhoff's first law (Law of Currents) for the two forms of circuit operation.

The two sets of nonlinear constraints (3), one for δ=0 and one for δ=1, model Kirchhoff's second law (Mesh Law) for the transmission network operating without and in simple contingency. The value of the parameter β (4) depends on the location of the contingent branch p, i.e.:

$$\begin{cases} se\ circuito\ ij \neq p\ \ então\ \beta = 0 \\ se\ circuito\ ij = p\ \ então\ \beta = 1 \end{cases} \qquad (4)$$

The parameter δ simulates the operating condition of the circuits in the network, and was inserted, along with the parameter β, to present the constraints in a compact form. δ=0 means that all circuits are operating, and δ=1 means that the network is with circuit p in contingency.

We therefore have two sets of constraints that together model the equality constraints of the problem: one that models the network operating without contingency and another that models the network operating with contingency.

In constraints (2) and (3) the meanings of the symbols are as follows: S- bus-branch incidence matrix, transposed, of the network; f- vector of active power flows in circuits ij with the network operating without contingency. Its elements are f_{ij}; f^n and f^p- active power flow vectors with the network operating without contingency and with circuit p unavailable (in contingency). Their elements are f_{ij}^n and f_{ij}^p; g^n and g^p- vectors of active power generations, with the network operating without contingency and with circuit p unavailable. Their elements are g_i^n and g_i^p $(i \in \Omega_g)$; Ω_g- set of generation bus; d- active loads vector; r^n and r^p- load shedding vectors with the grid operating without contingency and with circuit p unavailable. Its elements are r_b^n and r_b^p; γ_{ij}- susceptance of the added circuit on branch ij; n_{ij}^0- number of existing circuits on branch ij of the base grid; n_{ij}- number of circuits added on branch ij; θ_i^n, θ_j^n - angles of the voltages of bus i and j with the grid operating without contingency; θ_i^p, θ_j^p- angles of the voltages of bus i and j with circuit p unavailable.

II.3 INEQUALITY CONSTRAINTS

The inequality constraints used in the ABO_{N-1} optimizer are related to: the limits of capacities of circuit additions in the branches, the limits of active power flows in the circuits, new and existing, the limits of active powers produced in the generation bus and the limits of load shedding in the load bus.

Applying the parameters β and δ to the set of inequality constraints from [2], the constraints present the compact form indicated by inequations (5) to (10). The absolute values are necessary since the active power flows in the circuits can flow in two directions.

In constraints (5) to (10): $\bar{f}_{ij}$- maximum transmission capacity of circuit ij; $\bar{n}_{ij}$- maximum number of circuits that can be added in branch ij; $\bar{g}$- vector of maximum capacities of generators (its elements are $\bar{g}_i, i \in \Omega_g$).

$$(1-\beta)(1-\delta)\left|f_{ij}^n\right| + \delta\left|f_{ij}^p\right| \leq (1-\beta)(1-\delta)\gamma_{ij}\left(n_{ij}^0 + n_{ij}\right)\bar{f}_{ij} + \delta\left|f_{ij}^p\right|\left(n_{ij}^0 + n_{ij} - \beta\delta\right)\bar{f}_{ij} \qquad (5)$$

$$0 \leq (1-\delta)g^n + \delta g^p \leq \bar{g} \qquad (6)$$

$$0 \leq (1-\delta)r^n + \delta r^p \leq d \qquad (7)$$

$$0 \leq n_{ij} \leq \bar{n}_{ij},\ \ n_{ij}\ inteiro \qquad (8)$$

$$n_{ij}^0 + n_{ij} - 1 \geq\ 0, inteiro \qquad (9)$$

$$n_{ij} \geq 0\ e\ inteiro \qquad (10)$$

II.4 COMPLETE PROBLEM MODEL

The set of equations and inequations (1) to (10), which is based on the coupling between active power and the angle of the bar voltage [1], [2] is used by the ABO_{N-1} optimizer to model the TNESPS problem. The problem formulated in this way has the characteristics of a MINLP problem, whose resolution is quite complicated.

When the set of circuits to be added (n_{ij}) is known, problem (1) to (10) is reduced to a linear programming (LP) problem, and the ABO_{N-1} optimizer only checks whether this solution presents load shedding or not.

Applying the pairs of values (β=0, δ=0), (β=0, δ=1), (β=1, δ=0), (β=1, δ=1) to constraints (2), (3) and (5) to (10) yields fifteen constraints, five of which are equality and ten of which are inequality.

III. PROPOSED ALGORITHM

Write in detail the research project, including background and limitations. The selection of materials and methods, procedures and equipment must be justified so that the work can be reproduced. Modifications or new methods must be described in detail. You must clearly define the universe and specify how the sample was selected and why it is representative. Data processing represents the practical development of a theoretical basis, deriving the model equations to program the calculation algorithm, according to the need. In materials, they include the technical specifications and the quantities, the origin and, if necessary, the method for its elaboration.

III.1 CARACTERISTICS OF THE ABO ALGORITHM

This algorithm, as an optimization method, provides a search procedure belonging to swarm intelligence, based on the social behavior of animals. It was created by Odili et al. in 2015, inspired by the movements of buffaloes in the African savannahs in search of food.

As with most metaheuristic algorithms, the ABO algorithm also uses two strategies for exploring the search space: intensification which is directly related to exploring the region where the buffalo are grazing and diversification which is related to exploring new grazing regions. Each buffalo searches for the best grazing region to feed on, and updates its position in the grazing region according to the position of the best buffalo (leading buffalo) in the herd.

The ABO algorithm simulates three buffalo characteristics: i) memory, to not explore pasture regions already visited; ii) cooperation, to exchange information with other buffalo; and iii) intelligence, to issue alarm sounds "Waaa", which is used to warn of the presence of danger and lead the herd to other pasture regions, and alert "Maaa", which is used to encourage buffalo to continue grazing in the same region.

III.2 MAIN STEPS OF THE ABO ALGORITHM

The main steps that the ABO algorithm performs to position buffaloes in pastures are [11]:
Step 1: Randomly distribute each buffalo in the herd to different grassland regions of the savanna;
Step 2: Identify the best buffalo in the herd, using the evaluation function of the problem to be solved;
Step 3: Move each buffalo to a new nearest pasture region, considering its previous position and the position of the leading buffalo;
Step 4: Updates the new position occupied by each buffalo;
Step 5: Identifies the new best buffalo in the herd;
Step 6: Tests if the number of iterations has been reached. If yes, present the best distribution of buffalo in the grazing areas achieved. If no, move each buffalo to a new closest grazing region.

III.3 ANALOGY ABO X TNESPS PROBLEM

The search procedure used by the ABO algorithm, to optimize the distribution of African buffaloes in savanna grassland regions, can be compared to the search procedure used in the TNESPS optimization process, to distribute the circuits on the branches of a transmission system, by making the following analogies:

- Savannah grassland regions ↔ Candidate solutions space;
- Herd ↔ Candidate solutions (population);
- Buffalo ↔ Candidate solution;
- Leading buffalo ↔ Solution with the lowest overall cost;
- Quality of grazing ↔ Cost of the solution.

Figure 1 shows four candidate solutions of a hypothetical system of four branches and different amounts of circuits added per branch.

Branches	1-2	1-4	2-3	2-4	**Costs**	
Added Circuits	3	2	0	0	5	Solution 1
	0	**2**	**0**	**1**	**3**	**Solution 2**
	2	0	2	0	4	Solution 3
	1	2	1	2	6	Solution 4

Figure 1: Representation of candidate solutions.
Source: Authors, (2021).

According to the adopted analogy, it turns out that: i) The herd is composed of four buffaloes; ii) The buffaloes are located in pasture regions of different qualities; iii) The worst pasture region is region 4; iv) The leading buffalo is grazing region 2.

III.4 ABO$_{(N-1)}$ OPTIMIZER ALGORITHM

Figure 2 shows the main steps that the ABO$_{(N-1)}$ optimizer performs to solve the TNESPS problem.

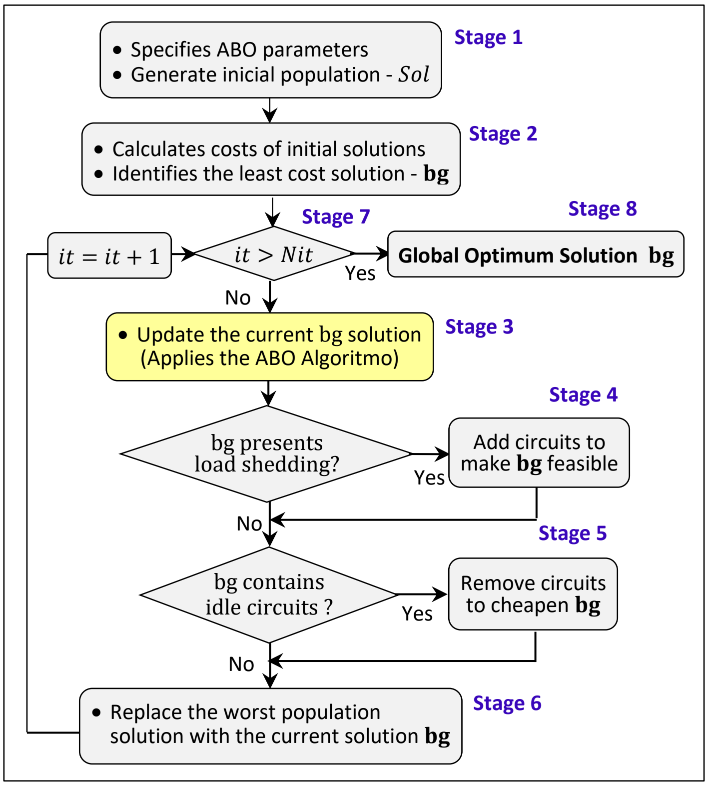

Figure 2: Flowchart of the ABO$_{(N-1)}$ optimizer.
Source: Authors, (2021).

➢ **Stage 1**

In this step the data for the ABO algorithm is provided, i.e., the learning factors lp1 and lp2 used in [14] to adjust the velocities of buffalo displacements from the pasture regions in search of food.

Since TNESPS is a non-convex problem of several local optimal solutions, the generation of the initial population has great influence on the quality of the initial solutions, and can help the search mechanism of metaheuristic algorithms [5], [6]. Thus, the ABO$_{N-1}$ optimizer generates the initial population (Sol), composed of NI solutions ($\{sol_1, \dots, sol_k, \dots, sol_{NI}\}$), as a function of the existing network topology, bar data, existing circuit data, candidate circuit data, and population size (NI), by performing two steps:

Step 1: Solve the transport model, represented by LP problem (11) to (16) [1], [39], [40], using the linprog function of MatLab, to obtain a solution (Sol_1).

$$Min\ v(sol_1) = \sum_{(i,j)\in\Omega_r} c_{ij} n_{ij} \tag{11}$$
$$s.a:$$
$$Sf + g = d \tag{12}$$
$$|f_{ij}| \le (n_{ij}^0 + n_{ij})\bar{f}_{ij} \tag{13}$$
$$0 \le g \le \bar{g} \tag{14}$$
$$0 \le n_{ij} \le \bar{n}_{ij} \tag{15}$$
$$n_{ij} \ge 0,\ inteiro \tag{16}$$

Step 2: It then generates the other (NI-1) initial solutions $\{sol_2, \dots, sol_{NI}\}$, randomly changing the positions and number of circuits of the branches of the solution sol_1, until the population size (NI) is reached.

This way of creating the initial population produces some infeasible solutions (solutions with load shedding), due to the simplified model (11) to (16), which considers only Kirchhoff's first law. However, these solutions are systematically eliminated over iterations.

- **Stage 2**

This step determines the cost of each initial solution (vc_k), the respective amounts load shedding (rc_k), and the least cost solution (bg_k). The cost of each solution (vc_k) is obtained by the product ($\sum c_{ij} n_{ij}$), since after the completion of step 1, the circuit set $\{n_{ij}\}$ of each solution (sol_k) of Sol and the respective costs (c_{ij}) are known. The load cutoff (rc_k), associated with each solution (sol_k), is obtained by solving LP problem (17) to (22) using the linprog function of MatLab.

$$Min\ \ rc_k = \sum_{(b)\in B}(r_b^n + r_b^p)\} \tag{17}$$
$$s.a:$$
$$Sf + r + g = d \tag{18}$$
$$f_{ij} - \gamma_{ij}(n_{ij}^0 + n_{ij})(\theta_i - \theta_j) = 0 \tag{19}$$
$$|f_{ii}| \leq (n_{ii}^0 + n_{ii})\bar{f}_{ii} \tag{20}$$
$$0 \leq g \leq \bar{g} \tag{21}$$
$$0 \leq r \leq d \tag{22}$$

- **Stage 3**

The purpose of this step is to update the current best solution (bg_k), modified in step 2, by performing two steps:

Step 1: Generate new solutions (sol_{k+1}), as a function of the current best solution (bg_k) and the solutions (sol_k), (w_k) and (pb_k), using equation (23), adapted from [13]. The rounding operator "round" and the absolute value operator "abs" were included because the number of circuits to be added in each branch of the system must always be integer and positive.

$$sol_{k+1} = round\{sol_k + abs[lp1.(bg_k - w_k) + lp2.(pb_k - w_k)]\} \tag{23}$$

The term $lp1.(bg_k - w_k)$ modifies the number of circuits of the current solution (bg_k), i.e., intensifies the search. Whereas the term $lp2.(pb_k - w_k)$ modifies the number of circuits of the current solution pb_k, i.e., diversifies the search.

Step 2: It obtains a candidate solution w_{k+1} updated as a function of the solution sol_{k+1} and the solution w_k by applying equation (24), adapted from [13].

$$w_{k+1} = round[(w_k + sol_{k+1})/\lambda)],\ \lambda = lp2/lp1 \tag{24}$$

In the first iteration of the ABO$_{(N-1)}$ optimizer the solution pb_k and w_k are equal to the solution sol_k and are updated at each iteration using the costs: $v(sol_{k+1})$, $v(sol_k)$, $v(pb_k)$, and $v(pg_k)$, according to the following rule:

- If $v(sol_{k+1}) < v(sol_k)$, the current solution sol_k is replaced by the solution sol_{k+1};
- If $v(sol_{k+1}) < v(pb_k)$, the current solution pb_k is replaced by the solution sol_{k+1};
- If $v(sol_{k+1}) < v(bg_k)$, the current solution bg_k is replaced by the solution sol_{k+1}.

After these updates only the current bg_k solution is submitted to the local improvement procedures to check if it presents load shedding or to check if its cost can be reduced. This best solution update procedure replaces the procedure used in AGCB [2].

- **Stage 4**

The purpose of this step is to make the current bg_k solution viable in case it has load shedding due to the update done in step 3. The feasibility is done by adding circuits in certain branches of the bg_k solution so that the load shedding is eliminated.

The choice of the most attractive circuit set $\{n_{ij}\}$ for addition is done using the sensitivity index (IS_{ij}) (25), proposed in the constructive heuristic algorithm (AHC) [41].

$$IS_{ij} = max\{n_{ij}.\overline{f}_{ij}; n_{ij} \neq 0\} \tag{25}$$

This algorithm solves, at each AHC step, the LP problem (26)-(33), to verify that the added circuits also meet the CC model. If not, the most attractive circuit is added to the base grid. In the LP problem model, the active power flows in the circuits are separated into two groups: flows in the existing circuits and from the circuits added by the iterative process of the algorithm.

In equation (27): S_0- matrix of incidence, transposed, bar-branch of the base network; S_1- matrix of incidence, transposed, bar-branch of the new network; f_0- vector of active power flows in the base network circuits, with the network without contingency; f_1- vector of power flows in the added circuits, with the network operating without any contingency. The parameters β and δ were introduced to compact the presentation of the model.

$$Min\ v(bg_k) = \sum_{(i,j)\in\Omega_r} c_{ij} n_{ij} \tag{26}$$
$$s.a:$$
$$(1-\delta)(S_0 f_0 + S_1 f_1 + g) + \delta(S_0 f_0^p + S_1^p f_1^p + g^p) = d \tag{27}$$
$$(1-\beta)(1-\delta)\left|f_{ij}^0 - \gamma_{ij} n_{ij}^0(\theta_i - \theta_j)\right| + \delta[f_{ij}^0 - \gamma_{ij}(n_{ii}^0 - \beta)(\theta_i^p - \theta_i^p)] = 0 \tag{28}$$
$$\left|f_{ij}^0\right| \leq n_{ij}^0 \bar{f}_{ij} \tag{29}$$
$$(1-\beta)(1-\delta)\left|f_{ij}\right| \leq n_{ij}\overline{f}_{ij} + \delta[\left|f_{ij}^p\right| \leq (n_{ij} - \beta)\bar{f}_{ij}] \tag{30}$$
$$0 \leq (1-\delta)g + \delta g^p \leq \bar{g} \tag{31}$$
$$0 \leq n_{ij} \leq \bar{n}_{ij},\ n_{ij}\ inteiro \tag{32}$$
$$n_{ij} - 1 \geq 0 \tag{33}$$

This model specifies that the basic network must satisfy both Kirchhoff's laws, and the branches formed by the new circuits satisfy only Kirchhoff's first law (Kirchhoff's second law is only applied to the basic network).

If solving this LP model results in $v(bg_k) = 0$ it means that $n_{ij} = 0, \forall(i,j) \in \Omega_r$, i.e., the system operates without overloads with the base topology circuits together with the added circuits. Since these circuits obey both Kirchhoff's laws, then the set of added circuits represents a feasible solution for the DC model.

- **Stage 5**

The purpose of this step is to reduce the cost of the current bg_k solution if it has unnecessary circuits due to the update performed in stage 3 through equations (23) and (24).

To check if there are any circuits added in bg_k that are redundant, they are sorted in descending order of cost, and then each of them is removed from the solution bg_k. If the removal, any of them, does not cause load shedding, it means that it is unnecessary and is eliminated. So only those circuits will be part of the current bg_k solution that if removed does not cause load shedding.

- **Stage 6**

This step is intended to verify whether the solution bg_k can enter the current population as a replacement for the one with the worst quality in terms of investment cost and load shedding.

Two conditions are imposed for the current solution bg_k to be accepted into the population: 1) bg_k must be different from all other solutions, i.e., it must present a circuit configuration that does not exist in the current population, and 2) bg_k must have a lower cost (if feasible) or lower load shedding (if infeasible) than all other solutions in the population.

Three situations are tested: (a) the solution bg_k is infeasible and there are infeasible solutions in the population, then bg_k replaces the highest load-cut solution; (b) the solution bg_k is feasible and there are infeasible solutions in the population, then bg_k replaces the highest load-cut solution; c) the solution bg_k is feasible and there are no infeasible solutions in the population, then bg_k replaces the current highest cost solution.

- **Stage 7**

In this step, the $ABO_{(N-1)}$ optimizer checks if the stopping criterion is reached, i.e., if the current number of iterations (it) is greater than the specified maximum value (Nit), then the iterative process is terminated.

- **Stage 8**

In this step, the $ABO_{(N-1)}$ optimizer presents the global optimal solution bg found in NI iterations, in terms of cost and number of circuits added in each branch of the base network to meet simple contingency.

IV. RESULTS AND DISCUSSIONS

This section presents the results obtained from applying the $ABO_{(N-1)}$ optimizer on three typical systems (G-6/15), IEEE-24/41 and SB-46/79), which have been widely used by researchers to test algorithms. The $ABO_{(N-1)}$ optimizer was implemented in MatLab language and simulations were performed on a computer with an Intel Core i5-7400T, 2.40 GHz, 8 GB RAM processor. The data used to adjust buffalo displacement velocities were lp1=0.9 and lp2=0.7 suggested in [14] to obtain a better balance between intensification and diversification processes of search space exploration.

Since the $ABO_{(N-1)}$ optimizer generates the candidate solutions randomly, there is the possibility of not always obtaining the same optimal solution at the end of iterations by performing several simulations. This possibility increases even more when the system has many bars (NB) and many branches (NR). Therefore, to minimize/eliminate this possibility, the population size (NI) and the number of iterations (Nit) were defined as a function of NB and NR, as shown in rules (34) and (35), except for the Garver system.

$$NI \approx NR \quad (34)$$
$$Nit > 1000(NR/NB) \quad (35)$$

IV.1 GARVER SYSTEM (G-6/15)

This small system has the following characteristics: demand and generation = 760 MW, NB= 6 (bus 6 isolated) and NR=15 (6 are existing). Data for existing and candidate bus and circuits are available in [37]. A maximum of four circuits per branch was allowed. This data results in a total of 515≃3x1010 possible combinations of circuit additions, indicating the enormous difficulty the algorithms face in solving TNESPS problems.

In the simulation of this system, a population size NI = 20 was used and Nit = 100 iterations were performed.

The global optimal solution found by the $ABO_{(N-1)}$ optimizer, without load shedding, contains 10 circuits and costs $298,000.

Figure 3 shows, in red lines, the planned circuits. The graphs in Figures 4 and 5, both produced by the $ABO_{(N-1)}$ optimizer, show the circuits added to the base network and the evolution of the total cost of the best solution.

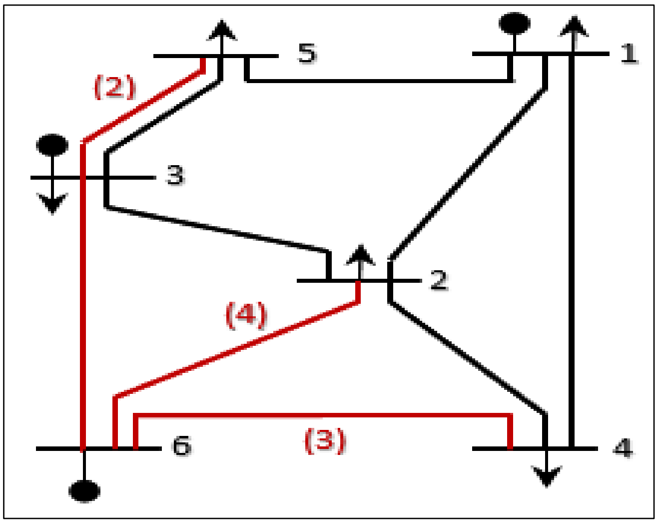

Figure 3: G-6/15 system -Planned network.
Source: Authors, (2021).

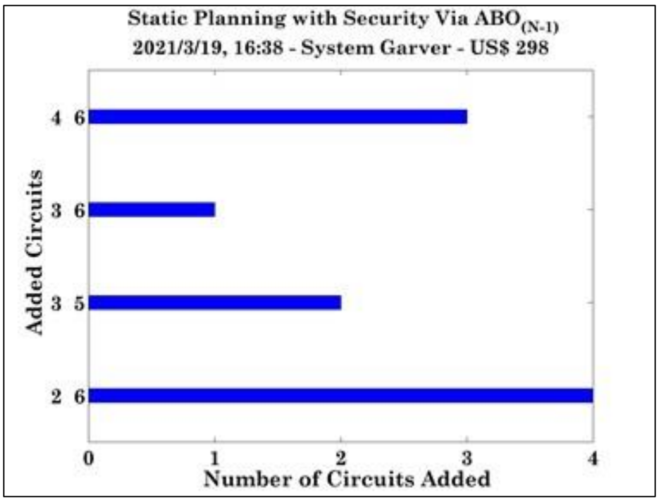

Figure 4: G-6/15 system - Planned circuits.
Source: $ABO_{(N-1)}$ optimizer, (2021).

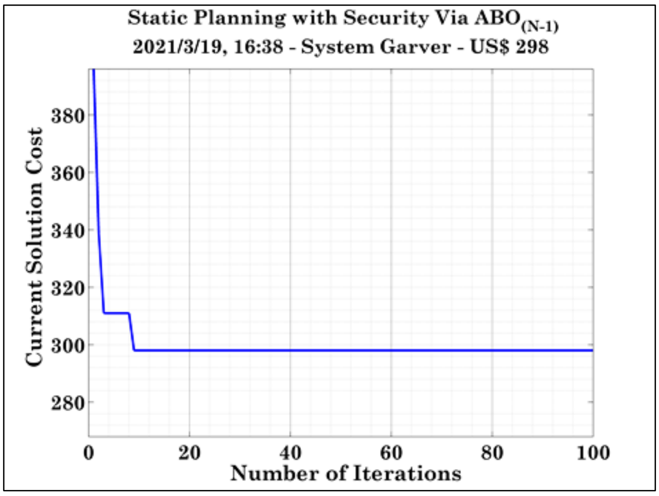

Figure 5: G-6/15 system: Cost evolution of the best solution.
Source: $ABO_{(N-1)}$ optimizer, (2021).

IV.2 IEEE SYSTEM (IEEE-24/41)

This system is one of the most used in testing new models and optimization techniques for TNESPS problems. It has a demand and generation= 8550 MW; NB=24 (generating units are connected on 10 bus and loads connected on 17 bars and there are no isolated bars); NR=41 (34 existing and 7 new). Data for bus and existing/candidate circuits are described in [42]. The generation data are from scenario G1.

A population size NI≈NR=40 was used to solve this system. Since the NR/NB ratio of this system is about 1.71, the number of simulations used was Nit=1800, since by rule (35), Nit must be greater than 1000(NR/NB).

In the simulation, branches with at most 4 circuits were allowed. This gives the total number of circuits to be analyzed 4x41=164 and the number of possible combinations of additions to the branches is about 541≃4.5x1028, i.e., 526 times larger than the number of possible combinations of additions to the G-6/15 system.

The global optimal solution that the ABO$_{(N-1)}$ optimizer found, without load shedding, contains 28 circuits, added on 17 existing branches (n_{01-05}=2, n_{03-09}=1, n_{03-24}=2, n_{04-09}=1, n_{05-10}=1, n_{06-10}=2, n_{07-08}=3, n_{10-11}=1, n_{11-13}=1, n_{14-16}=2, n_{15-16}=1, n_{15-21}=1, n_{15-24}=2, n_{16-17}=3, n_{16-19}=2, n_{17-18}=2 and n_{21-22}=1) and costs $1,071 million.

This same solution was obtained with the following data: a) NI=40 and Nit=2000, b) NI=40 and Nit=5000, c) NI=50 and Nit=2000. Figure 6 shows, in filled red lines, the 28 circuits (the dotted lines are the candidate circuits).

Figure 7 shows the circuits of the best solution obtained with the ABO$_{(N-1)}$ optimizer and Figure 8 shows the evolution of the cost of the best solution, where convergence was reached at the 1199th iteration.

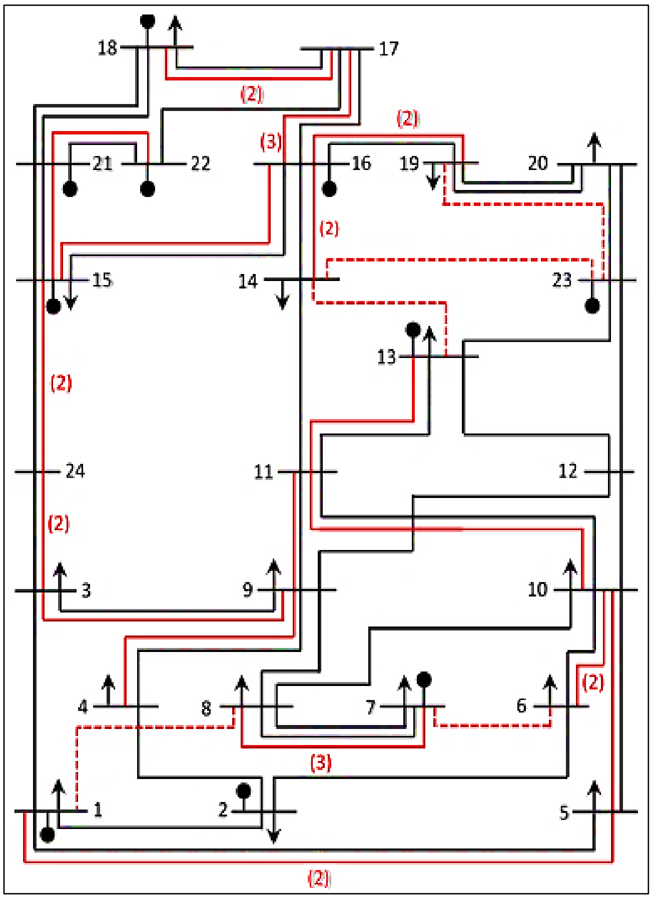

Figure 6: IEEE-24/41 system – Planned network.
Source: Authors, (2021).

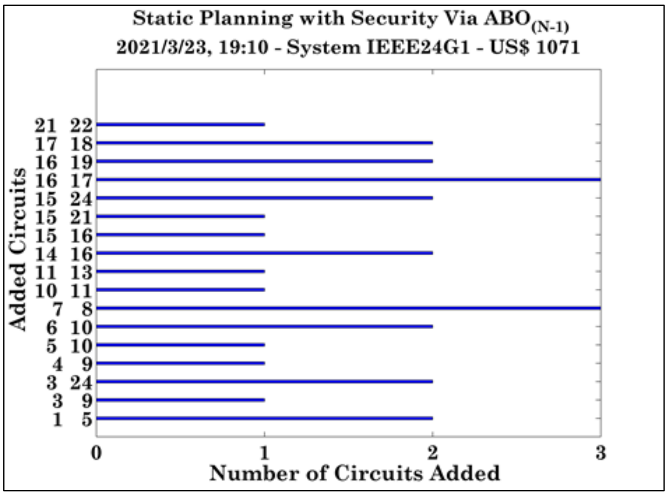

Figure 7: IEEE-24/41 system - Planned circuits.
Source: ABO$_{(N-1)}$ optimizer, (2021).

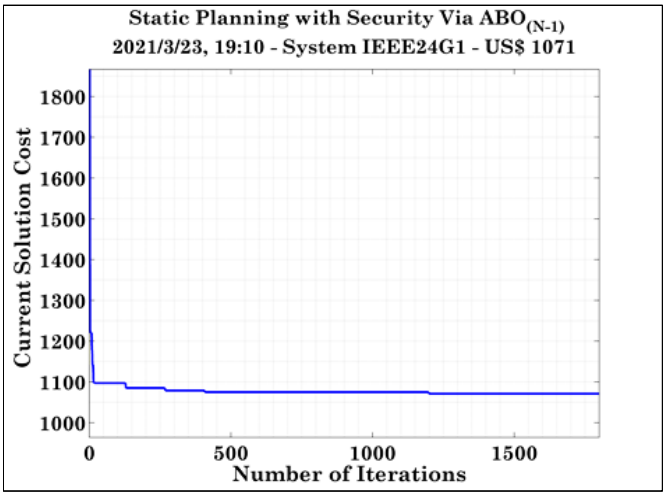

Figure 8: IEEE-24/41 system - Cost evolution of the best solution.
Source: ABO$_{(N-1)}$ optimizer, (2021).

IV.3 SOUTH BRAZILIAN SYSTEM (SB-46/79)

Monticelli et al., 1982 [43], was the first to use this real system to validate an interactive TNESPS solution method and since then it has been used to validate several methods. This system is an old configuration of the power system in the southern region of Brazil, and is therefore a good test for the ABO$_{(N-1)}$ optimizer.

The data for this system are: demand and generation=6880 MW; NB=46 (generators are connected on 12 bus and loads on 19 bus); NR=79 (47 existing/32 new). Existing circuits are connected on bus operating at 500 kV and 230 kV voltages). The bus data and existing and candidate circuit data are described in [40].

This system has 479/541=8x1018 times more possible combinations of circuit additions than the IEEE-24/41 system, and almost twice as many buses (1.71=41/24), and a greater number of isolated bus (11 bus).

The global optimal solution found by the ABO$_{(N-1)}$ optimizer, without load shedding, contains 28 circuits, connected in 18 branches, (n_{02-05}=1, n_{12-14}=1, n_{19-21}=1, n_{17-19}=1, n_{14-22}=1, n_{32-43}=1, n_{20-21}=2, n_{42-43}=3, n_{46-06}=2, n_{19-25}=1, n_{21-25}=1, n_{31-32}=2, n_{28-31}=2, n_{31-41}=1, n_{40-45}=1, n_{24-25}=3, n_{40-41}=1 and n_{05-06}=3), and costs $356,086 million.

Figure 9 shows, in red lines, the 28 circuits. Figure 10 shows the circuits of the solution produced by the ABO$_{(N-1)}$ optimizer in all 6 simulations.

Figure 11 shows the evolution of the cost of the best solution, where convergence was reached at the 398th iteration.

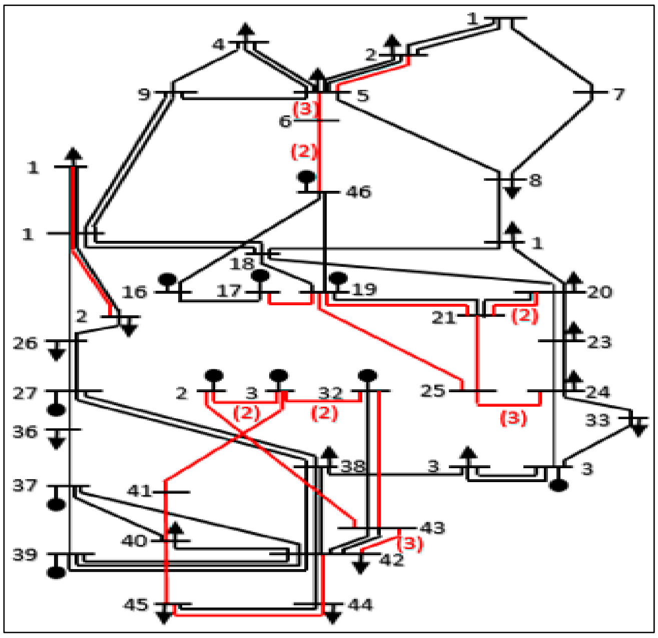

Figure 9: SB-46/79 system – Planned network.
Source: Authors, (2021).

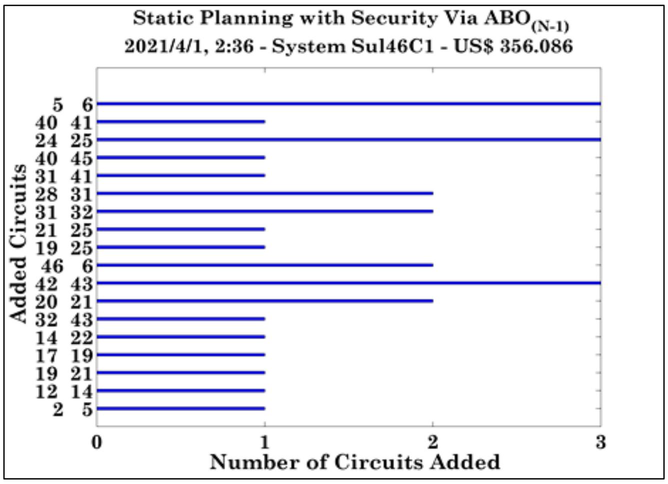

Figure 10: SB-46/79 system - Planned circuits.
Source: $ABO_{(N-1)}$ optimizer, (2021).

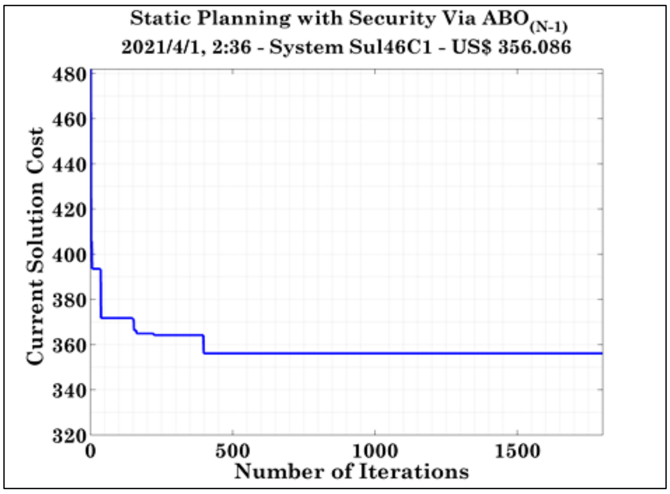

Figure 11: SB-46/79 system - Cost evolution of the best solution.
Source: $ABO_{(N-1)}$ Optimizer, (2021).

V. CONCLUSIONS

This paper presents a new metaheuristic algorithm, called the $ABO_{(N-1)}$ optimizer, for solving TNESPS problems with the network modeled by a DC power flow. An AC power flow model and other metaheuristics can be used in place of the ABO algorithm. To solve this complex nonlinear, non-convex optimization problem with integer and mixed variables, an algorithm based on the movement of African buffaloes in search of food was used.

To reduce costs of feasible candidate solutions and to enable candidate solutions with load shedding, Chu-Beasley's local improvement procedures used in a genetic algorithm were used. Such procedures, in addition to improving the local and global exploration of the search space, transform the MINLP problem into a PPL problem.

The results achieved with the $ABO_{(N-1)}$ optimizer, on three transmission systems widely used as benchmarks (Garver-6 bus, IEEE-24 bus, the South Brazilian-46 bus), attest to its ability to solve TNESPS optimization problems efficiently.

The solutions for the larger systems required longer computational times, due to the larger number of possible combinations and the need to compute more power flows in all branches of the network arising from removing one circuit from each branch at a time.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: João Ricardo Paes de Barros.
Methodology: João Ricardo Paes de Barros.
Investigation: João Ricardo Paes de Barros.
Discussion of results: João Ricardo Paes de Barros.
Writing – Original Draft: João Ricardo Paes de Barros and Dimitri Albuquerque de Barros.
Writing – Review and Editing: João Ricardo Paes de Barros and Dimitri Albuquerque de Barros.
Resources: João Ricardo Paes de Barros and Dimitri Albuquerque de Barros.
Supervision: João Ricardo Paes de Barros.
Approval of the final text: João Ricardo Paes de Barros.

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