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# Artificial Immune Systems applied to the reconfiguration of electrical power distribution networks for energy loss minimization

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ABSTRACT

This paper presents a methodology for the reconfiguration of radial electrical distribution systems based on the bio-inspired meta-heuristic Artificial Immune System to minimize energy losses. The proposed approach can handle this combinatorial mixed integer problem of nonlinear programming. Radiality and connectivity constraints are considered as well as different load levels for planning the system operation. For this purpose, improvements to an algorithm in the literature are proposed to better accommodate the features of the problem and to improve the search process. The algorithm developed is tested in well-known distribution systems.



## 1. Introduction

The reconfiguration of electrical distribution systems (EDS) is an alternative to reduce technical losses in electrical network feeders. This option must be considered when planning the operation due to the high variable costs associated with these systems [1].

The problem of reconfiguration consists of the definition of the states (open or closed) of the maneuverable switches attached to certain sections of the distribution network [2]. These maneuver devices include (i) sectionalizing or normally closed (NC) switches and (ii) tie or normally open (NO) switches. This process can be applied to determine a radial and connected network topology that minimizes energy losses and meets operational constraints [3]. To solve this problem, models of mixed integer programming are used, involving discrete variables associated with the states of the maneuver devices and continuous variables associated with the limits of the voltage in busbars and branch flows, for example. These models must consider the combinatorial nature of the problem because the number of possible solutions grows exponentially with the number of discrete variables [4]. In addition, the radial and connected features of the distribution network present additional complexity for the solution techniques.

To reduce the search space associated with reconfiguration problems, heuristic-based methods have been proposed in the literature [5–12]. Refs. [8,9] present heuristic algorithms that start from a meshed topology and perform a sequential opening of switches to determine a radial topology with minimal losses using power flow and optimal power flow (OPF), respectively. Refs. [10–12] propose the application of heuristic techniques together with the analysis of sensitivity indexes. In [10], an index based on the derivative of the active power loss in relation to the impedance of the branches is proposed, while the proposed indexes in [11,12] are based on Lagrange multipliers obtained from an OPF model.

Ref. [13] presents a heuristic algorithm that starts from a meshed network and performs a sequential opening of the network loops to obtain a radial topology with minimal losses. This method uses the information of the active and reactive breakpoint nodes for the reconfiguration. These nodes are particular buses where the branch active and reactive power flows converge, respectively. Only the branches entering in the breakpoint nodes are chosen as candidates to be opened, increasing the efficiency of the approach. The breakpoint nodes are determined each time a loop is opened by a power flow computation.

The application of meta-heuristics in combinatorial problems leads to an efficient search in the solution space. These techniques allow the transition between subspaces of the feasible region, as well as a more focused search in each subspace. Algorithms based on meta-heuristics, such as Genetic Algorithms [14–18], Simulated Annealing [19,20], Artificial Ant Colony [21] and Tabu Search [22,23], have been used to solve the problem of EDS reconfiguration. With the same purpose in mind, Ref. [24] presents an algorithm based on Artificial Immune Systems to reduce active

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power losses. In [25], a method based on the bacterial foraging optimization algorithm is proposed for distribution network reconfiguration and loss minimization. Some modifications have been developed to retain the radial structure and reduce the searching requirement. Ref. [26] presents a method for the reconfiguration and phase balancing of EDS based on a bacterial foraging approach using a fuzzy multi-objective function.

The genetic algorithm proposed in [16] for distribution networks reconfiguration to obtain minimal losses considers the operational constraints referred to the lines and substations power flow capacity limits, node voltage limits, as well the radiality constraint. This algorithm uses the edge window decoder encoding technique for network representation and building up spanning trees, as well as efficient genetic operators in order to explore the search space. Ref. [17] presents an adaptive imperialist competitive reconfiguration algorithm to minimize real power losses and to improve the voltage profile. A heuristic prohibited zone method is proposed to enhance the convergence behavior of the algorithm and to check the radiality constraint. Furthermore, two other meta-heuristics, the genetic algorithm and the artificial ant colony, are implemented in [17] for the reconfiguration problem.

Due to the high dimension of the problem of EDS reconfiguration, few studies consider more than one load level of the daily load curve [11,12,27–30]. Most studies consider only one load period, and thus, they do not guarantee an optimal topology for other load levels. Ref. [31] proposes a harmony search algorithm with dynamic programming to determine an annual feeder reconfiguration scheme by considering the costs for switching from a configuration to another configuration, as well as time-varying variables, such as load profiles.

Ref. [18] also considers more than one time interval for the EDS reconfiguration to minimize the energy losses. In addition, this reference includes multiple conflicting objectives by using Pareto front analysis. These objectives are the network losses and the energy not supplied. A genetic algorithm based solver is proposed to construct and update the best-know Pareto front. This optimization approach provides an automatic support for the decision maker to identify the preferable solution in the final Pareto front.

In light of the lines of research on this subject and the requirements to troubleshoot the EDS reconfiguration, the investigation of new techniques based on meta-heuristics is promising. Following these lines, this paper proposes a methodology based on the bio-inspired technique called Artificial Immune Systems (AIS) for reconfiguration by seeking minimal energy losses and considering different load levels in the context of operation planning. To achieve this goal, modifications are proposed in a clonal selection algorithm for optimization from the literature [24,32]. These improvements aim to better accommodate the constraints and the features of the reconfiguration problem, including electrical network connectivity and radiality. Each candidate topology is evaluated through a power flow calculation. The main purposes are to investigate the application of the Artificial Immune System for reconfiguration while considering load curves, to evaluate the impact of representing different load levels and of the number of levels defined from typical daily curves in the reconfiguration problem. Tests with systems referenced in the literature prove the advantages of the method.

## 2. Proposed methodology

### 2.1. Theoretical fundamentals of the proposed technique

AIS consists of a technique inspired by innate immune systems with applications that include pattern recognition, machine-learning and optimization [33]. An important element of the innate immune system is the B cell, which produces antibodies in response to pathogenic agents or antigens. Each B cell produces a single type of receptor or antibody, which can recognize a specific antigen. The complementarity between the receptor and a given antigen define the binding affinity between the respective B cell and the pathogenic agent.

When the affinity is higher than a limit value, the antigen-receptor binding is accomplished, which activates the B cell. Then, the process called affinity maturation begins, in which mechanisms such as clonal selection, cloning and somatic hypermutation enable the organism to produce varieties of B cells with high affinity to the antigen. After this process, B cells in their active state produce antibodies at high rates to fight the pathogenic agent.

The clonal selection principle establishes the proliferation of antibodies that recognize an antigen. In AIS, this principle can be compared to the search for the solution of an optimization problem. In this case, there is no explicit antigen to be recognized but rather an objective function to be maximized or minimized [32]. Thus, the affinity of the B cell or of the antibody is given by the objective function. Within this context, according to the clonal selection principle, the cells with more affinity are cloned and submitted to a two-phased affinity maturation. In one of these phases, the joint action of the clonal selection and somatic hypermutation mechanisms enables local exploration of the solution space. In the other phase, the mechanism of new cell generation, or receptor editing, allows the process to expand to new solution regions through the introduction of population diversity. Thus, both stages execute complementary functions for affinity maturation.

AIS can be applied in problems of constrained, multimodal and combinatory optimization [34]. Through antibody cloning and clone affinity maturation, it is possible to find multiple optimal and suboptimal solutions. In other words, each cloned antibody leads to a local search in a subspace of the solution region [32]. The depth of this search is given by the respective number of clones.

In the innate immune system, cells or antibodies that recognize the molecules of their own organism (self-antigens) are produced from time to time, which represents an attack against the organism. Therefore, these cells must be identified and eliminated through a mechanism called ‘negative selection’, which can be modeled in AIS.

### 2.2. Modeling of the reconfiguration problem

The optimization problem associated with the reconfiguration of distribution systems to minimize energy losses was formulated in [12], as shown here.

$$\text{Min OBF} = \sum_{u=1}^{NT}\left[\sum_{k=1}^{NB}\left[\sum_{m\in\Omega k}[\text{CH}_{km}\cdot(ce_u.T_u.L_{km,u})]\right]\right] \tag{1}$$

subject to

$$Pg_{k,u} - Pl_{k,u} + \sum_{m\in\Omega k}\text{CH}_{km}\cdot P_{km,u} = 0 \tag{1.1}$$

$$Qg_{k,u} - Ql_{k,u} + \sum_{m\in\Omega k}\text{CH}_{km}\cdot Q_{km,u} = 0 \tag{1.2}$$

$$L_{km,u} = g_{km}\cdot\left[V_{k,u}^2 + V_{m,u}^2 - 2.V_{k,u}.V_{m,u}\cdot\cos(\theta_{km,u})\right] \tag{1.3}$$

$$\text{CH}_{km} = 0 \text{ ou } 1 \tag{1.4}$$

$$\overline{Z}^{\min} \leqslant \overline{Z}_u \leqslant \overline{Z}^{\max} \tag{1.5}$$

where OBF, objective function; $u$, given load level; NT, total number of load levels; NB, total number of busbars; $\Omega k$, set of busbars directly connected to busbar $k$; $CH_{km}$, value associated with maneuverable switch $k$–$m$; $ce_u$, energy price (US$/kW h) for load level $u$; $T_u$, time interval the EDS operating at load level $u$; $L_{km,u}$, active power loss of branch $k$–$m$ at load level $u$; $Pg_{k,u}$, active power generation at busbar $k$ at load level $u$; $Pl_{k,u}$, active power load at busbar $k$ at load level $u$; $P_{km,u}$, active power flow through branch $k$–$m$ at load level $u$; $Qg_{k,u}$; reactive power generation at busbar $k$ at load level $u$; $Ql_{k,u}$; reactive power load at busbar $k$ at load level $u$; $Q_{km,u}$; reactive power flow through branch $k$–$m$ at load level $u$; $g_{km}$, conductance of branch $k$–$m$; $V_{k,u}$, voltage magnitude at busbar $k$ at load level $u$; $\theta_{km}$; phase angle between busbars $k$ and $m$ at load level $u$; $\overline{Z}_u$, vector containing the other OPF variables that have lower and upper limits on the load level u, and $\overline{Z}^{\min}, \overline{Z}^{\max}$, vectors containing the lower and upper limits, respectively, of the variables $\overline{Z_u}$.

Eq. (1) defines the objective function of the reconfiguration problem, which represents the minimization of the cost of the total energy losses in the system at all load levels to be analyzed. The energy price (US$/kW h) given by $ce_u$ can reflect the difference in pricing during each load level $u$. Other objectives such as minimal costs of switching and distributed generators and capacitors placement [12], as well as the phase balancing [26], the improvement of the network voltage profile [17] and the minimization of the energy not supplied [18] can be considered for planning the distribution systems operation. However, the objective function in (1) has a unique term referred to the energy loss minimization because this paper aims to evaluate the effectiveness of the AIS technique to obtain a radial network with minimal losses and to evaluate the impact of the daily load curves in light of this line of research. It can be noticed that other objectives can be included in the proposed formulation by modeling and adding new terms to the *OBF* in (1). Therefore, one important aspect is that some objectives are also achieved even if the objective function does not comprise them in an explicit way. For example, the system voltage profile is also improved by using the function in (1), as it will be shown in the test results.

Eqs. (1.1) and (1.2) correspond to the constraints of the balance of the active and reactive power, respectively. Eq. (1.3) is used to calculate the active power loss in branch $k$–$m$.

Constraint (1.4) shows that switch modeling in the formulated problem implies the treatment of the discrete variables $CH_{km}$. The unit value for $CH_{km}$ indicates the closed branch $k$–$m$, while $CH_{km} = 0$ indicates an open branch. Due to the presence of these variables, the reconfiguration problem has a combinatory and large-scale nature for real systems. All other optimization variables have their limits established in (1.5). This set of constraints includes the nodal voltage limits.

### 2.3. Proposed algorithm – CLONR

The algorithm proposed in this work for EDS reconfiguration – called CLONR – is based on the algorithm of clonal selection described in the literature, called CLONALG [24,32], in which the fundamentals of the bio-inspired technique AIS [33,34] are applied to combinatory problems.

As previously described, there is no antigen to be recognized but an objective function to be optimized in the application of AIS to optimization problems. In reconfiguration, this function corresponds to the cost of the energy loss in the distribution network, given by Eq. (1), which must be minimized. Therefore, in this case, the antibody affinity is inversely proportional to the objective function formulated in (1). The antibody, in turn, is associated with the topology of the distribution network. The antibody affinity represents the quality of the corresponding topology in terms of the cost of the energy loss; that is, the lower the cost, the better the quality of the respective topology and the higher the affinity of the associated antibody are. The size of each antibody ($L$), that is, the number of attributes of an antibody, is equal to the number of maneuverable switches in the system. Each attribute represents the state of a switch and receives the value 0 (open switch) or 1 (closed switch) to meet constraint (1.4). Table 1 summarizes the representation proposed for the reconfiguration problem via AIS, which seeks minimal energy losses.

The system shown in Fig. 1 [24] will be used as an example, where all 12 branches have coupled maneuverable switches ($S_1$–$S_{12}$). The switches $S_2$ to $S_9$, $S_{11}$ and $S_{12}$ are closed, and the switches $S_1$ and $S_{10}$ are open.

The antibody associated with the configuration of Fig. 1 is represented as follows:

$$Ab_1 = \begin{bmatrix} {}^{S_1} & {}^{S_2} & {}^{S_3} & {}^{S_4} & {}^{S_5} & {}^{S_6} & {}^{S_7} & {}^{S_8} & {}^{S_9} & {}^{S_{10}} & {}^{S_{11}} & {}^{S_{12}} \\ 0 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & 1 & 1 \end{bmatrix} \tag{2}$$

It is important to mention that the $Ab_1$ size ($L$) is equal to 12; in other words, the antibody size is equal to the total number of maneuverable switches in the network. Fig. 2 shows the flowchart of the proposed algorithm. The steps of this algorithm are described below.

(1) Generation of an initial repertoire of antibodies $P^*$.

This step is only executed in the first generation ($g = 1$) of the CLONR algorithm. The generation of the initial repertoire of antibodies is performed through a branch exchange process [5,6,35] in the base topology, that is, in the initial radial configuration of the system. This procedure is based on the premise that the base topology is high quality in terms of energy loss compared to all possible radial configurations. This aspect was observed for all optimized distribution systems and is in accordance with Ref. [36], which considers the problem of a minimal spanning tree. According to this reference, the trees that share the largest number of edges with the base tree have the greatest possibility of belonging to the solution set. Thus, the base topology consists of a good starting point to derive new configurations that are candidates for the solution. Therefore, the search process is oriented to the most attractive regions of the space of feasible solutions, increasing the efficiency of the algorithm.

Therefore, based on the base topology, '$Nab$ – 1' configurations are derived through branch exchanges, forming a repertoire of $Nab$ antibodies or candidate solutions together with the former. This process ensures that the new '$Nab$ – 1' configurations are radial and connected, such as the base topology. That is, meshed or disconnected topologies, which are unfeasible for the reconfiguration problem, are excluded from the initial solution space, which increases the efficiency of the proposed algorithm.

As an example, considering again the system exemplified in Fig. 1, where its base topology is given by $Ab_1$ and supposing that the repertoire $P^*$ is composed of three antibodies ($Nab = 3$), Eq. (3) presents $P^*$ with $Ab_1$ and the configurations $Ab_2$ and $Ab_3$ derived from $Ab_1$.

$$\begin{bmatrix} Ab_1 : 0^{S_1} & 1^{S_2} & 1^{S_3} & 1^{S_4} & 1^{S_5} & 1^{S_6} & 1^{S_7} & 1^{S_8} & 1^{S_9} & 0^{S_{10}} & 1^{S_{11}} & 1^{S_{12}} \\ Ab_2 : 1 & 0 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & 1 & 1 \\ Ab_3 : 0 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & 1 & 1 & 1 \end{bmatrix} \tag{3}$$

**Table 1**
Problem representation via AIS.

| AIS element | Problem equivalent |
|---|---|
| Antibody | Network configuration |
| Antibody size ($L$) | Total number of switches |
| Attribute | Switch state (0 ou 1) |
| Affinity | Inverse of loss cost (1) |

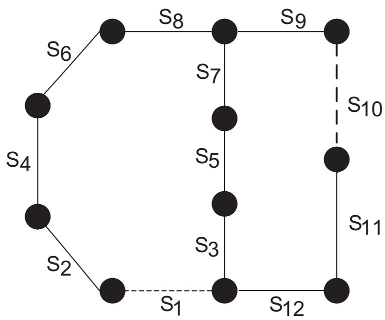


**Fig. 1.** Example system.

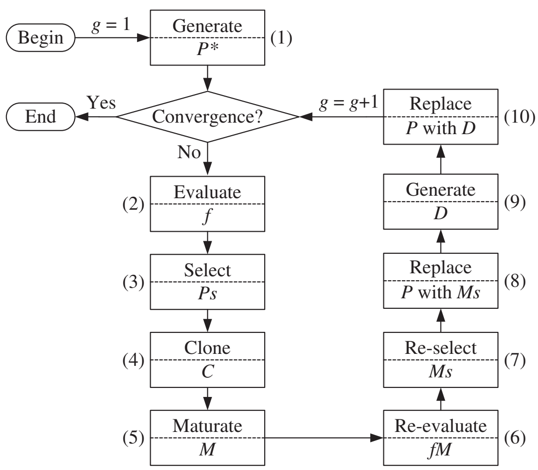


**Fig. 2.** Flowchart of the proposed algorithm, CLONR.

The branch exchange performed to generate $Ab_2$ consists of the closing of switch $S_1$ and the opening of $S_2$. The antibody $Ab_3$, in turn, was derived through the opening of $S_9$ together with the closing of switch $S_{10}$. The repertoire $P^*$ is represented by a matrix $[Nab \times L]$.

When deriving new candidate topologies, some exchanges may generate unfeasible solutions. For example, based on topology $Ab_1$, the states of switches $S_1$ and $S_9$ cannot be exchanged because this exchange would lead to a loop being formed by switches $S_1$–$S_8$, in addition to the busbar disconnection between switches $S_9$ and $S_{10}$. Therefore, the process of branch exchanges requires a previous network analysis based on graph theory to define the branches that connect all busbars and do not form loops [37,38].

After the formation of the initial repertoire of antibodies $P^*$, the algorithm proceeds to Step (2) with the current repertoire $P = P^*$.

(2) Evaluation of affinity $f$ of the antibodies from $P^*$.

The affinity of an antibody is inversely proportional to the respective cost of energy loss, given by Eq. (1). The active power loss in each load level, Eq. (1.3), is determined by the calculation of power flow in the network while observing constraints (1.1) and (1.2).

(3) Selection of the best antibodies from P∗.

In this step, the antibodies of $P$ that present the greatest affinities $f$ are selected for cloning. These antibodies, which are all different from each other, form set $Ps$. The maximum size of set $Ps$ is given by the parameter $n$. In some cases, $Ps$ may present a smaller number of antibodies than $n$ due to one of the following situations:

- One or more of the $n$ antibodies of $P$ with the greatest affinities correspond to unfeasible solutions, which may occur due to the unfeasibility of the EDS operation for the respective topologies, even though they are radial and connected. This unfeasibility can be identified through the divergence in power flow calculation. In other unfeasible cases, this calculation converges, but limit constraints (1.5) are not observed when the variables of $\overline{Z_u}$ are monitored for all load levels $u$. Therefore, these unfeasible topologies are not included in set $Ps$, which prevents the local exploration of subspaces associated with unfeasibility to increase the algorithm efficiency.
- One or more antibodies present loss costs, given by the objective function $OBF$ of Eq. (1), larger than the base topology cost. These antibodies are not included in set $Ps$ either. This procedure is based on the concept of minimum affinity [36], in which the affinity of an antibody selected for cloning must be larger than a lower limit. In the proposed CLONR algorithm, this limit is given by the inverse of the $OBF$ of the base topology. Hence, the search process is directed to the subspaces with the largest potential to reduce the cost of the base topology and gains efficiency.

(4) Cloning of the antibodies of set Ps.

The antibodies selected in the previous step and included in set $Ps$ are cloned, forming a new configuration set: $C$. In the proposed CLONR algorithm, the number of antibody clones is proportional to its normalized affinity. The proportional cloning consists of one of the improvements proposed in this paper to the CLONALG algorithm for optimization in the literature [24,32], which suggests that all antibodies have the same number of clones, regardless of the affinity.

In the CLONR algorithm, the number of clones of a given antibody $i$ is calculated according to Eq. (4).

$$Nc(i) = round(\beta \cdot f^*(i)) \tag{4}$$

where Nc($i$), total number of clones associated with the antibody $i$; $round$(.), round operator to the nearest integer value; $\beta$, control parameter for the cloning process, and $f^*(i)$, affinity of antibody $i$ (normalized).

With Eq. (4), it is possible to obtain the number of clones that best represents the antibody affinity because this number is proportional to the normalized value of the affinity ($f^*$), as calculated through Eq. (5).

$$f^*(i) = 1/\{1 + \exp[-(f(i) - \bar{f})/\delta^*]\} \tag{5}$$

where $f(i)$, affinity of antibody $i$; $\bar{f}$, arithmetic affinity of antibodies associated with set $Ps$, and $\delta^*$, antibody affinity standard deviation of $Ps$.

The sigmoid normalization proposed in this work, Eq. (5), consists of another improvement to the CLONALG algorithm [24,32]. The sigmoid normalization presented good behavior for the problem of reconfiguration and led to a more adequate distribution of the values of the $OBF$ formulated in Eq. (1). The normalized affinity of a generic clone $ic$ of antibody $i$ is equal to the normalized affinity of $i$ ($f^*(ic) = f^*(i)$).

(5) Somatic hypermutation of antibodies of $C$.

The purpose of somatic hypermutation, or mutation, is to insert and maintain the diversity of the repertoire $P$ of antibodies and to increase the affinity of candidate solutions. The application of this mechanism results in the formation of a mature clone population, $M$. The probability of mutation of a clone $ic$ of the set $C$, formed in the previous step, is inversely proportional to its normalized affinity $f^*(ic)$, as per Eq. (6) [24,32].

$$p(ic) = \exp(-\rho \cdot f^*(ic)) \quad (6)$$

where $p(ic)$, mutation probability of clone $ic$, which must be in the interval of [0,1], and $\rho$, control parameter for the hypermutation process.

The parameter $\rho$ controls the damping of the exponential function formulated in Eq. (6). The higher the value of $\rho$, the more damped this function is according to Fig. 3 [32].

In Fig. 3, the probability of mutation $p$ is inversely proportional to the normalized affinity $f^*$. In addition, the higher the value of parameter $\rho$, the lower the probability of mutation for the same affinity value is.

After the calculation of the probabilities according to Eq. (6), a random number in the interval [0,1] is generated for each clone of set $C$. If the random number for the clone $ic$ is lower than the probability $p(ic)$, this clone will undergo mutation and will be inserted in the new set $M$ with modifications. Otherwise, the clone $ic$ will be inserted in set $M$ without variation.

The modification introduced in a mutated clone consists of branch exchanges, that is, given the system in Fig. 1, a mutation in antibody $Ab_3$, Eq. (3), can be given, for example, by a simple branch exchange through the opening of switch $S_3$ together with the closing of $S_1$, resulting in the following matured clone:

$$Ab_{3-M} = \begin{bmatrix} S_1 & S_2 & S_3 & S_4 & S_5 & S_6 & S_7 & S_8 & S_9 & S_{10} & S_{11} & S_{12} \\ 1 & 1 & 0 & 1 & 1 & 1 & 1 & 1 & 0 & 1 & 1 & 1 \end{bmatrix} \quad (7)$$

It should be emphasized that the mutation process is based on branch exchanges and knowledge of the branches that connect all busbars and do not form loops, which is investigated in Step (1) [37,38], to guarantee the radiality and connectivity of mutated configurations. That is, the mutation cannot exchange, for example, switches $S_1$ and $S_9$, as previously described.

Additionally, to increase the efficiency of the CLONR algorithm, this work proposes the use of high mutation generations intercalated with normal mutation generations through the variation of parameter $\rho$. CLONR begins with $\rho = \rho_1$. As this algorithm evolves, another value can be used, $\rho = \rho_2$, where $\rho_2 < \rho_1$, provided that (i) the best solution of repertoire $P$ remains unaltered during a number of generations given by $g^*$ or (ii) the diversity of repertoire $P$ is inferior to a limit (*limd*). This second condition is based on the optimization algorithm via AIS proposed in [36].

Both conditions for $\rho$ to be equal to $\rho_2$ represent the stagnation of the algorithm in regions of the search space. Therefore, to avoid premature convergence in one of these regions, the value of $\rho$ ($\rho = \rho_2$) is reduced, increasing the probabilities of mutation (see Fig. 3). When the previous conditions (i) and (ii) are no longer valid, the initial value of $\rho$ is reestablished ($\rho = \rho_1$). Thus, generations with lower mutation rates ($\rho = \rho_1$) are intercalated with high mutation generations ($\rho = \rho_2$), as suggested in [39].

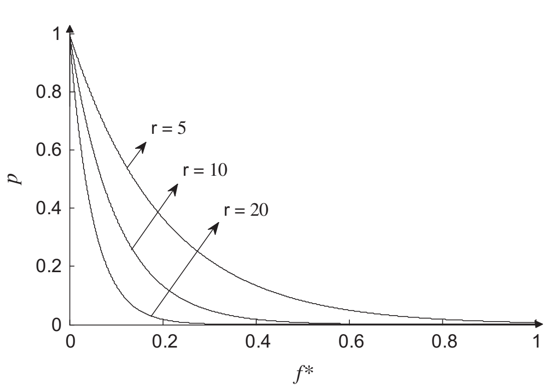


**Fig. 3.** Function for the mutation probability.

The diversity of antibodies population (*div*) verified in the previous condition (ii) is calculated according to Eq. (8) [36].

$$div = Nab\_dist/Nab \quad (8)$$

where *Nab_dist* is the number of unique individuals, that is, individuals that are not repeated in the repertoire *P*.

(6) Evaluation of affinity *fM* of antibodies of *M*.

Process described in Step (2).

(7) Selection of the best antibodies of *M*.

Process described in Step (3), forming set *Ms.* in Step (7).

(8) Substitution of antibodies of *P* with antibodies of *Ms*.

In this step, the antibodies of set *Ms*, formed in the previous step, replace an equal number of antibodies with the lowest affinities of *P*.

(9) Receptor editing.

Generation of *d* antibodies, as described in Step (1), to form set *D*.

(10) Substitution of antibodies of *P* with antibodies of *D*.

In this step, *d* antibodies with the lowest affinities of the repertoire *P* are replaced with antibodies from set *D*, which was formed in the receptor editing. This mechanism allows the introduction of greater diversity among candidate solutions and the investigation of new regions of the search space that may still be unexplored.

After Step (10), the generation counter ($g$) is incremented, and the convergence criterion is verified. This criterion is met when at least one of the following conditions is reached:

- the number of generations reaches a limit value (*gmax*), or
- the best solution of the repertoire *P* remains unaltered during a number of generations given by *gest*.

If the convergence criterion is met, the CLONR algorithm is finalized. Otherwise, the optimization process returns to Step (2).

As general considerations about the proposed CLONR algorithm, it is emphasized that the generation of candidate solutions in Steps (1) and (9) and the mutation in Step (5) prevent the introduction of mesh and/or disconnected configurations in the repertoire of antibodies *P*. These procedures are inspired by the mechanism of negative selection of the innate immune system previously described, that is, topologies that are unfeasible due to the formation of loops in the network and/or due to busbar isolation are associated with antibodies that recognize self-antigens and, therefore, must be eliminated.

## 3. Load level modeling

The problem of reconfiguration formulated in (1) includes the representation of different load levels of the system. Three load levels are considered as an example. In this case, it is necessary to establish the following variable vectors of the power flow: $\overline{Z_L}$ (light load), $\overline{Z_M}$ (medium load) and $\overline{Z_P}$ (heavy load). These variables must be accommodated in the solution matrix structure of this problem, as shown in Eq. (9).

$$\begin{bmatrix} \Delta PQ_{\overline{Z_L}} \\ \Delta PQ_{\overline{Z_M}} \\ \Delta PQ_{\overline{Z_P}} \end{bmatrix} = \begin{bmatrix} J_{\overline{Z_L},\overline{Z_L}} & & \\ & J_{\overline{Z_M},\overline{Z_M}} & \\ & & J_{\overline{Z_P},\overline{Z_P}} \end{bmatrix} \cdot \begin{bmatrix} \Delta_{\overline{Z_L}} \\ \Delta_{\overline{Z_M}} \\ \Delta_{\overline{Z_P}} \end{bmatrix} \quad (9)$$

where $J_{\overline{Z}_u\overline{Z}_u}$, Jacobian sub-matrix associated with the load level $u$; $\Delta PQ_{\overline{Z}_u}$, Mismatch vector of active and reactive power associated with the load level $u$, and $\Delta_{\overline{Z}_u}$, step vector of the variables associated with the load level $u$.

At all levels $u$, the same switch has a unique state CH (0 or 1). Therefore, these levels are attached to each other through switching decisions.

## 4. Example system

The 33-bus system shown in Fig. 4 [6] is considered to illustrate the application of the CLONR algorithm proposed in this work. The branches represented by solid lines are attached to normally closed maneuverable switches (NC), except for $S_1$ because the opening of this branch would result in the disconnection of the whole network from the substation (S/S). The dashed lines represent the tie or normally open switches (NO). In all, there are 37 branches and 36 maneuverable switches, of which five are tie switches.

The application of the CLONR algorithm is exemplified here for this 33-bus system. To simplify this tutorial case, only one load level, 1.0 pu, and the minimization of the active power loss are considered. In the base topology of Fig. 4, this loss is 202.68 kW, which defines the *OBF* value of Eq. (1) for this configuration. The S/S voltage is maintained at the value of 1.0 pu, and the lower voltage limit in all other busbars is 0.85 pu.

*Step (1)*: The initial repertoire of antibodies ($P^*$) is composed of 72 candidate configurations (*Nab* = 72), including the base topology. This value is equal to double the number of maneuverable switches according to Table 2. As previously described, the configurations of $P^*$ are derived from the base topology. To demonstrate the efficacy of this procedure, Table 3 presents the losses associated with the best and the worst configurations and the average loss of the feasible configurations of repertoire $P^*$ for two initialization conditions: (i) the proposed condition, in which radial and connected configurations are derived from the base topology, and (ii) the random generation of radial and connected configurations.

In both previous conditions, the algorithm convergence was reached by the number of generations without changing the best solution, given by the parameter *gest* in Table 2. In Table 3, the generation of $P^*$ in the proposed condition (i) leads to the formation of a better-quality repertoire. As a consequence, the number of generations for convergence in the condition (i) ($g$ = 25) was lower than the number obtained in the condition (ii) ($g$ = 28). This difference tends to be higher for larger distribution networks, as observed for other systems tested.

Fig. 5 presents the evolution of the objective function of Eq. (1) for the proposed condition (i). All other steps of the algorithm are also described here for this condition.

For the proposed condition (i), the CLONR algorithm is not sensitive to the initial topologies of the repertoire *P*. In other words, provided that these candidate topologies are derived from the base topology, the efficiency of the algorithm is the same, regardless of the initial repertoire, as observed for all systems tested.

*Steps (2) and (3)*: In Step (2), the values of *OBF* of Eq. (1) are determined for each antibody of *P* through the calculation of the power flow for each antibody. Table 3 presents the minimum, medium and maximum losses obtained after this calculation in the first generation ($P = P^*$).

In Step (3), the best configurations of *P* are selected to compose set *Ps*. In the first generation ($g$ = 1), 43 configurations were identified as different from each other. Out of these configurations, 28 present an *OBF* higher than the base topology *OBF* and/or violation of the voltage limit. Therefore, set *Ps* was formed by the 15 remaining configurations, whose minimum, medium and maximum losses are presented in Table 4.

It is emphasized that the criterion of formation of set *Ps* limits the search space efficiently because it leads to a reduction of the candidate configurations set, in which the maximum loss is equal to the base topology *OBF* and the operation does not present a voltage violation.

**Table 2**
Parameters of the proposed algorithm, CLONR.

| Nab | 2 N cm | $\rho$ | $\rho_1 = 1.0$; $\rho_2 = 0.2$ |
|---|---|---|---|
| $g_{max}$ | 100 | gest | 20 |
| $\beta$ | 20 | $g^*$ | 5 |
| $n$ | Nab | limd | 50% |
| $d$ | 5% Nab | | |

**Table 3**
Losses in two conditions of $P^*$ generation.

| | Condition (i) | Condition (ii) |
|---|---|---|
| Minimum loss (kW) | 153.49 | 175.92 |
| Average loss (kW) | 272.89 | 374.56 |
| Maximum loss (kW) | 893.67 | 1061.00 |

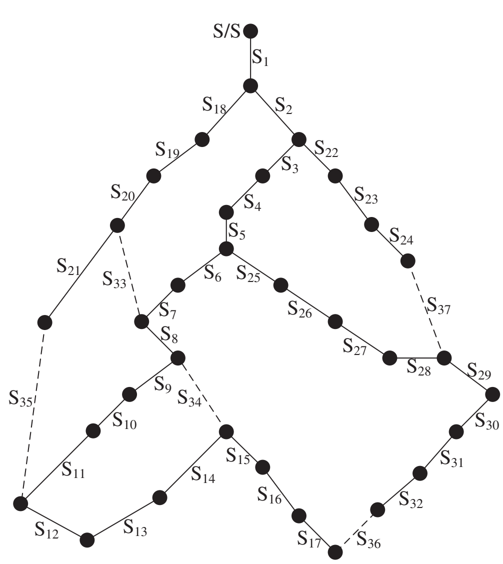


**Fig. 4.** 33-Bus system.

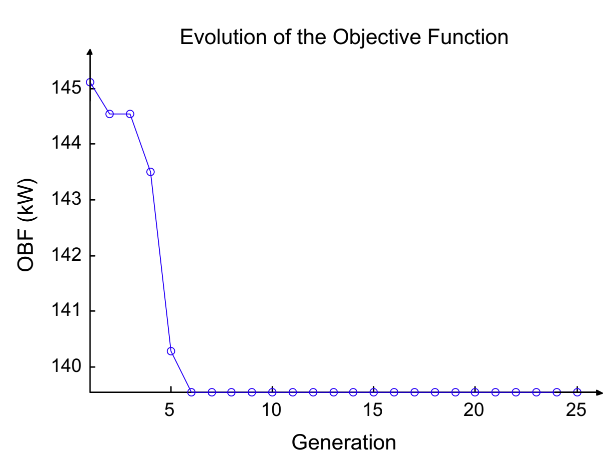


**Fig. 5.** Evolution of the objective function – *OBF*.

*Step (4)*: In this step, the numbers of clones (*Nc*) are calculated for each configuration of set *Ps* through Eq. (4). These numbers are presented in Table 5.

Table 5 verifies that the number of clones of each configuration of *Ps* is proportional to its affinity; that is, the smaller the loss, the greater the *Nc* is. A total of 150 clones are obtained by summing the values of *Nc* to compose set *C*.

*Step (5)*: The probability of mutation is calculated for each configuration of set *C* through Eq. (6). Out of these 150 configurations of *C*, 91 were mutated based on the calculation of their probabilities. Out of the 15 clones of configuration-1 of Table 5 and 5 were mutated, which represents a 33% mutation rate. In turn, the four clones of configuration-15 present a higher mutation percentage (75%). This difference is expected because configuration-1 has greater affinity and thus must suffer less mutation. The set of matured clones *M* is composed of the same number of topologies of *C*.

*Steps (6)–(8)*: Step (6) calculates the *OBF* values for each antibody of the set of matured clones, *M*.

In Step (7), the best configurations of *M* are selected to compose set *Ms*. In the first generation, 15 configurations were selected in this step.

In Step (8), the configurations of *Ms*. replace the worst 15 topologies of repertoire *P*. After the substitution, the losses of this updated repertoire are presented in Table 6.

After the application of the maturation process, the best configuration associated with minimum loss in Table 6 has better quality than the previous ones in Table 3, which demonstrates the capacity for evolution of the CLONR algorithm.

*Steps (9) and (10)*: In Step (9), four antibodies are generated from the base topology to compose set *D*, whose losses are given in Table 7.

To introduce diversity in repertoire *P*, the configurations of Table 7 replace the four worst topologies of this repertoire in Step (10), regardless of the affinity. The introduction of these configurations in *P* may lead to new regions, which may be more promising.

During the evolutionary process, the repertoire diversity was lower than the limit, given by the parameter *limd* in Table 2, in generation $g = 5$. Therefore, the parameter $\rho$ was changed to $\rho_2$, leading to a high mutation generation to avoid premature convergence at point $OBF = 143.51$ kW. In fact, this change allowed the algorithm to leave this suboptimal point and to evolve to a minimum loss of 139.55 kW in $g = 6$, thus reestablishing the value of $\rho = \rho_1$. In the following generation, the process described occurred again; that is, the diversity was below the limit at point $OBF = 139.55$ kW. However, new generations of high mutation did not lead to an additional loss reduction. Thus, convergence was obtained by the number of generations (*gest* in Table 2) with no evolution of the optimal point, as shown in Fig. 5.

Table 8 presents the solution obtained by proposed CLONR algorithm and by other methods referred to in the literature, which shows that this algorithm can determine compatible solutions. According to [8,9], the solution found by CLONR corresponds to the global optimal point for this case, as determined through an exhaustive search. The bold values in Tables 8, 12, 14 and 15 correspond to the switches that has changed between the presented solutions.

## 5. Results

This section presents the results obtained through the application of the CLONR algorithm proposed for the problem of EDS reconfiguration. For this purpose, six case studies were performed, including four systems referred to in the literature: the 33-bus system [6] with a modified load [8,9], the 94-bus system [41], the 119-bus system [42], and the 476-bus system [8,9]. In all cases, the voltage at the substation was maintained at 1.0 pu. Additionally, for each case, ten executions of the proposed algorithm were performed to evaluate the robustness of the method because the search process is probabilistic in nature.

In Cases-1, 2, 3 and 6, only one load level was considered to show the effectiveness of the proposed algorithm by comparing this approach with other methods. Cases-4 and 5 included more than one load level. However, the energy prices in these cases have the same value for all the load levels to reproduce the same conditions of the literature and to evaluate the impact of the daily curves on the reconfiguration problem from the load variation point of view.

The results of the proposed CLONR algorithm were validated through the comparison with previous research in the literature. The references used for this comparison were (i) Case-1: [8,9], (ii) Case-2: [10,41], (iii) Case-3: [10], (iv) Case-4: [12], (v) Case-5: [10,41], (vi) Case-6: [8,9].

The tests were performed using an Intel(R) Core(TM)2 microcomputer with a Quad CPU Q8200 2.33 GHz, 8 GB RAM memory and MATLAB® software version 7.7.0.471 (R2008b).

### 5.1. Case-1

This case consists of the minimization of the active power loss by considering a single load level (1.0 pu) for the 33-bus system of Fig. 4. To evaluate the behavior of the CLONR algorithm proposed when facing changes in the busbar loads, a load change of the system was considered according to Refs. [8,9]. The lower volt-

**Table 4**
Losses of set *Ps* in generation $g = 1$.

| Minimum loss (kW) | Average loss (kW) | Maximum loss (kW) |
|---|---|---|
| 153.49 | 175.67 | 202.68 |

**Table 5**
Number of clones for each configuration of *Ps*.

| Config. | Loss (kW) | *Nc* | Config. | Loss (kW) | *Nc* |
|---|---|---|---|---|---|
| 1 | 153.49 | 15 | 9 | 177.28 | 9 |
| 2 | 153.99 | 15 | 10 | 180.04 | 8 |
| 3 | 155.13 | 15 | 11 | 196.42 | 5 |
| 4 | 156.53 | 15 | 12 | 198.71 | 5 |
| 5 | 156.79 | 15 | 13 | 200.13 | 5 |
| 6 | 158.39 | 14 | 14 | 202.18 | 4 |
| 7 | 168.20 | 11 | 15 | 202.68 | 4 |
| 8 | 175.13 | 10 | | | |

**Table 6**
Losses of set *P*, generation $g = 1$, Step (8).

| Minimum loss (kW) | Average loss (kW) | Maximum loss (kW) |
|---|---|---|
| 145.11 | 203.35 | 360.76 |

**Table 7**
Losses of set *D*, $g = 1$.

| Loss-1 (kW) | Loss-2 (kW) | Loss-3 (kW) | Loss-4 (kW) |
|---|---|---|---|
| 569.75 | 156.79 | 156.79 | 231.21 |

**Table 8**
Solutions for the 33-bus system.

| Topology | Losses (kW) | Opened Switches |
|---|---|---|
| Base | 202.68 | $S_{33}$, $S_{34}$, $S_{35}$, $S_{36}$, $S_{37}$ |
| [9,40] | 140.28 | $S_7$, $\mathbf{S_{10}}$, $S_{14}$, $S_{32}$, $S_{37}$ |
| CLONR, [7,8,10] | 139.55 | $S_7$, $\mathbf{S_9}$, $S_{14}$, $S_{32}$, $S_{37}$ |

age limit was 0.85 pu. Table 9 presents the solution obtained in the ten executions of CLONR and the solution presented in Refs. [8,9], including the open switches and the minimum voltage ($V_{min}$) of the system in each solution. The number between parentheses after the voltage value corresponds to the busbar in which minimum voltage occurs. The proposed algorithm obtains a solution of better quality for this case, which consists of the global optimal solution determined via an exhaustive search in [8,9]. CLONR was proven to be robust in this case because the global optimal solution was obtained in the ten executions performed.

### 5.2. Case-2

The system used in this case, from Taiwan Power Corporation (TPC) [41], has 94 busbars, 11 feeders of 11.4 kV, two substations and 96 branches. Each of these branches was considered to be attached to a maneuverable switch. The number of tie switches (NO) is 13. The loss in the base topology shown in Fig. 6 is 531.99 kW. The analysis aimed to minimize the loss of the active power for a single load level (1.0 pu) and a voltage limit of 0.90 pu. The solution obtained for this case in the ten executions of the proposed algorithm was the same as that obtained by other methods presented in the literature according to Table 10. The minimum voltage is 0.93 pu at busbar 9 for the base topology and 0.95 pu at busbar 71 for the optimal configuration obtained.

### 5.3. Case-3

This study case aimed to evaluate the performance of the CLONR algorithm for a distribution network with a larger number of maneuverable switches. For this purpose, the 119-bus system [42], composed of one substation and 133 branches attached to maneuverable switches, 15 of which are NO switches, was used. The lower voltage limit was 0.85 pu. Table 11 presents the solutions found in the literature for this system, followed by the different solutions obtained in the ten executions of the CLONR algorithm. The minimum voltages are 0.87 pu at busbar 77 for the base topology and 0.93 pu at busbar 111 for all other topologies.

In Table 11, the number between parentheses in the first column indicates the number of executions in which each CLONR solution was obtained. That is, in the ten executions of this algorithm, the solution Sol-1 was obtained five times, Sol-2 was obtained twice and Sol-3, three times. Therefore, the CLONR solution is better than the solution found in the literature [10] in 70% of the executions (Sol-1 and Sol-2). Different configurations are obtained for this system due to the high number of suboptimal solutions, given the features of this network. The quality of the solutions determined by CLONR shows the potential of its application to the reconfiguration problem.

### 5.4. Case-4

The purpose of this case is to evaluate the impact of the representation of different load levels in the reconfiguration problem. The system used was the 33-bus [6]. The analysis was based on the realistic daily load curves obtained from [43]. The unit cost

**Table 9**
Solutions for the modified 33-bus system.

| Topology | Losses (kW) | Opened switches | $V_{min}$ (pu) |
|---|---|---|---|
| Base | 339.66 | $S_{33}$, $S_{34}$, $S_{35}$, $S_{36}$, $S_{37}$ | 0.87(17) |
| [8,9] | 207.94 | $S_7$, $S_{10}$, $S_{14}$, $S_{28}$, $S_{36}$ | 0.93(17) |
| CLONR | 198.11 | $S_9$, $S_{14}$, $S_{28}$, $S_{32}$, $S_{33}$ | 0.93(13) |

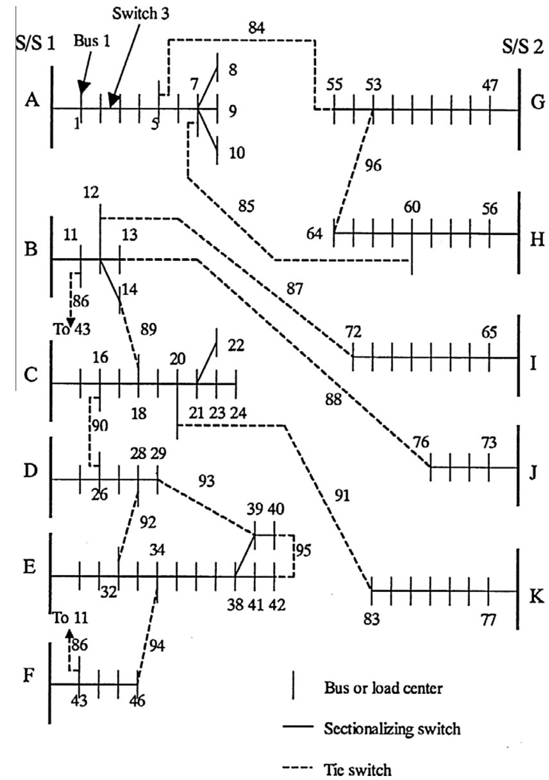


**Fig. 6.** 94-Bus system.

of energy loss, $ce_u$, at all load levels $u$ was 0.5 US$/kW h. The total operational time was six months, and the minimum voltage allowed was 0.90 pu. For the base topology, the minimum voltage was 0.92 pu at busbar 32, and the total energy loss was 936.01 MW h, which resulted in a loss cost of US$ 468,006.20.

To evaluate the impact of the load levels considered in the reconfiguration, the algorithm proposed was executed for four segmentation conditions of the daily curves in [43], 24, 12, 6 and 3 load levels. That is, for these conditions, $NT$ = 24, 12, 6 and 3, respectively; see problem (1). The daily periods considered were

- $NT$ = 24: curve discretization 24 h a day;
- $NT$ = 12: curve discretization at 2, 4, 6, 8, 10, 12, 14, 16, 18, 20, 22, and 24 h;
- $NT$ = 6: curve discretization at 4, 8, 12, 16, 20, and 24 h;
- $NT$ = 3: curve discretization at 8, 16, and 24 h.

Table 12 shows that the solutions may vary according to the number of levels considered. As expected, the solutions obtained when the curves are represented with more levels tend to be of better quality due to a more realistic representation of the system. For each condition established, ten executions of the CLONR algorithm were performed, leading to the same solution for each condition. These results were the same as those obtained in [12] for the same analysis conditions.

### 5.5. Case-5

The purpose of this case was to evaluate the impact of representing daily load levels in the EDS reconfiguration. The system used was the one with 94 busbars used in Case-2 [41]. The analysis was based on typical load curves of a real distribution system obtained from [11,12] to represent different load levels. The feeders of this system, shown in Fig. 6, were divided into two groups, as

**Table 10**
Solutions for the 94-bus system.

| Topology | Losses (kW) | Opened Switches |
|---|---|---|
| Base | 531.99 | $S_{84}$, $S_{85}$, $S_{86}$, $S_{87}$, $S_{88}$, $S_{89}$, $S_{90}$, $S_{91}$, $S_{92}$, $S_{93}$, $S_{94}$, $S_{95}$, $S_{96}$ |
| CLONR, [10,41] | 469.88 | $S_7$, $S_{13}$, $S_{34}$, $S_{39}$, $S_{42}$, $S_{55}$, $S_{62}$, $S_{72}$, $S_{83}$, $S_{86}$, $S_{89}$, $S_{90}$, $S_{92}$ |

**Table 11**
Solutions for the 119-bus system.

| Topology | Losses (kW) | Opened Switches |
|---|---|---|
| Base | 1,296.60 | $S_{119}$ – $S_{133}$ |
| [10] | 870.33 | $S_{24}$, $S_{27}$, $S_{35}$, $S_{40}$, $S_{43}$, $S_{52}$, $S_{59}$, $S_{72}$, $S_{75}$, $S_{96}$, $S_{99}$, $S_{110}$, $S_{123}$, $S_{130}$, $S_{131}$ |
| CLONR Sol-1 (5) | 853.58 | $S_{24}$, $S_{26}$, $S_{35}$, $S_{40}$, $S_{43}$, $S_{51}$, $S_{59}$, $S_{72}$, $S_{75}$, $S_{96}$, $S_{98}$, $S_{110}$, $S_{122}$, $S_{130}$, $S_{131}$ |
| CLONR Sol-2 (2) | 862.26 | $S_{24}$, $S_{26}$, $S_{35}$, $S_{40}$, $S_{43}$, $S_{51}$, $S_{59}$, $S_{71}$, $S_{74}$, $S_{77}$, $S_{96}$, $S_{110}$, $S_{122}$, $S_{130}$, $S_{131}$ |
| CLONR Sol-3 (3) | 870.91 | $S_{24}$, $S_{26}$, $S_{35}$, $S_{40}$, $S_{43}$, $S_{51}$, $S_{62}$, $S_{72}$, $S_{74}$, $S_{77}$, $S_{83}$, $S_{110}$, $S_{122}$, $S_{126}$, $S_{131}$ |

**Table 12**
Evaluation of the load level impact: the solutions of CLONR and from [12].

| Number of levels | $NT = 24$; 12 | $NT = 6$; 3 |
|---|---|---|
| Opened switches | $S_7$, $S_9$, $S_{14}$, $S_{32}$, $\mathbf{S_{37}}$ | $S_7$, $S_9$, $S_{14}$, $S_{32}$, $\mathbf{S_{28}}$ |
| Losses (MW h) | 641.32 | 643.97 |
| Loss cost (US$) | 320,659.70 | 321,983.70 |
| $V_{min}$ (pu) | 0.94 (31) | 0.95 (31) |

**Table 13**
Load Levels for the 94-bus system.

| Level | N1 | N2 | N3 | N4 |
|---|---|---|---|---|
| Multiplicative factor of load (pu) – Group-1 | 0.50 | 0.80 | 0.95 | 0.70 |
| Multiplicative factor of load (pu) – Group-2 | 0.80 | 0.95 | 0.60 | 0.70 |
| Duration (h) | 2920 | 3650 | 730 | 1460 |
| Energy loss cost – $ce_u$ (US$/kW h) | 0.06 | 0.06 | 0.108 | 0.06 |

in [11]: Group-1 (feeders A-F going out from substation S/S1) and Group-2 (feeders G-K from S/S2). The load curves used for these two groups were different from each other [12] to represent different types of consumers in the groups. These curves were segmented into four levels (N1–N4), as shown in Table 13. The lower voltage limit was 0.90 pu.

Table 14 presents the optimal solution obtained in ten executions of the CLONR algorithm in the previous conditions, that is, considering the four load levels simultaneously in both feeder groups. This solution is compared to the solutions of other methods [10,41], which consider only one load level (1.0 pu).

It is observed that the solution of the CLONR algorithm is of better quality than the solutions obtained in [10,41], which do not represent load curves in the reconfiguration problem. This result shows the importance of representing the load levels of the system [11,12]. The robustness of the algorithm proposed is confirmed by the ten executions performed, which led to the same optimal solution.

**Table 14**
Solutions for the 94-bus system with load levels.

| Configuration | Base | CLONR | [10,41] |
|---|---|---|---|
| Opened switches | $S_{84}$ – $S_{96}$ | $S_7$, $S_{13}$, $S_{34}$, $S_{39}$, $S_{42}$, $\mathbf{S_{84}}$, $S_{62}$, $S_{72}$, $\mathbf{S_{91}}$, $S_{86}$, $S_{89}$, $S_{90}$, $S_{92}$ | $S_7$, $S_{13}$, $S_{34}$, $S_{39}$, $S_{42}$, $\mathbf{S_{55}}$, $S_{62}$, $S_{72}$, $\mathbf{S_{83}}$, $S_{86}$, $S_{89}$, $S_{90}$, $S_{92}$ |
| Total losses (MW h) | 2684.89 | 2412.59 | 2424.50 |
| Loss cost (US$) | 173,640.09 | 155,260.14 | 155,773.75 |
| $V_{min}$ (pu) | 0.95 (9) | 0.97 (9) | 0.97 (71) |

**Table 15**
Solutions for the 479-bus system.

| Topology | Losses (kW) | Opened switches | $V_{min}$ (pu) |
|---|---|---|---|
| Base | 202.73 | $S_{10643}$, $S_{5380}$, $\mathbf{S_{1167}}$, $S_{10647}$ | 0.95(213) |
| CLONR, [8,9] | 161.02 | $S_{10643}$, $S_{5380}$, $\mathbf{S_{2942}}$, $S_{10647}$ | 0.96(213) |

**Table 16**
Computation times of CLONR.

| Case | Average Time (seconds) |
|---|---|
| 1 | 16.9 |
| 2 | 160.0 |
| 3 | 704.1 |
| 4 ($NT = 24$) | 203.4 |
| 4 ($NT = 12$) | 102.7 |
| 4 ($NT = 6$) | 50.9 |
| 4 ($NT = 3$) | 32.3 |
| 5 | 272.8 |
| 6 | 845.6 |

### *5.6. Case-6*

This case aimed to evaluate the CLONR algorithm applied to a real medium-sized system [8,9]. This system has 476 busbars, two urban aerial feeders of 13.8 kV, 479 branches and 22 maneuverable switches, four of which are NO switches. In this case, the analysis aimed to minimize the power loss for a single load level (1.0 pu) with a lower voltage limit of 0.94 pu. Table 15 presents the solution obtained in the ten executions of CLONR, which is the same solution found in [8,9] and then validates the algorithm proposed for this system.

As previously described, the base topology is a good quality solution for several systems, which can be confirmed in Table 15, because the only difference between this topology and the optimal solution obtained is related to the status of one maneuverable switch.

Table 16 presents the computation times for the execution of the proposed CLONR algorithm for each case. These values correspond to the processing time averages for the ten executions performed in each case.

The CLONR algorithm uses search mechanisms such as cloning, somatic hypermutation and receptor editing. These mechanisms, if applied well, lead to an efficient search within the solution space and, consequently, to acceptable computation times for EDS operation planning, as shown in Table 16. The good quality demonstrated for the solutions in the study cases, together with the non-prohibitive times for the problem requirements, confers the desired efficiency to the method proposed. The representation of the load levels in reconfiguration, Cases-4 and 5, does not introduce a substantial increase in the processing time. Therefore, the application of the proposed methodology makes it possible to include important aspects while keeping computation times within a range that is feasible for operation planning.

## 6. Conclusions

This work proposed the application of the bio-inspired optimization technique called Artificial Immune Systems (AIS) to reconfigure radial distribution networks and to minimize the total energy losses in these systems. For this purpose, the CLONR algorithm was proposed based on an algorithm found in the literature in which the fundamentals of the AIS technique are applied. Given its characteristics, this technique can be classified as meta-heuristics, a set of methods that are suitable for solving complex and large-scale problems, such as the reconfiguration of real systems. The improvements proposed for the algorithm referenced in the literature aim to better adapt the fundamentals of the technique to the characteristics of the problem. It is emphasized that the application of a clonal selection algorithm for reconfiguration while considering load curves is unprecedented. Based on the results obtained, it can be conclude that

- The quality of the solutions for the tested systems was shown to be compatible with those found in the literature. In some cases, the application of the proposed algorithm provided quality gains in comparison to other methods.
- The proposed model considered constraints that are important for the problem, such as network radiality and connectivity, and adequate system voltage levels.
- The proposed algorithm presented a computation effort that is feasible for the operation planning of distribution systems, making it possible to represent more than one load level. Furthermore, the AIS technique is suitable for the use of parallel processing, which can reduce computation times, favoring its application in large systems. Finally, the implementation of CLONR in C++ can also accelerate the reconfiguration process.

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