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Hybrid-Adaptive Differential Evolution with Iterated Local Search for Long-Term Transmission Network Expansion Planning Optimization

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ABSTRACT

The increasing sophistication of transmission network expansion planning (TNEP) can be attributed to several evolving factors. These include the uncertain nature of renewable energy sources, the introduction of new market regulations and participants, and ongoing demand amplification in line with the increasing integration of electric vehicles and energy storage systems. The TNEP is a complex optimization problem that finds the optimal number and location of new transmission lines to satisfy system demand. In this work, we propose a hybrid-adaptive differential evolution with an iterated local search algorithm to solve this combinatorial problem and evaluate the performance of multiple acceptance criteria for solution selection in the iterative process for an 87-bus north-northeast Brazilian transmission system. Results showed that the HyDE-ILS strategies reduced the total costs by around 5% to 6% compared to HyDE on average.

Keywords: acceptance criteria, hybrid-adaptive differential evolution, iterated local search, transmission network expansion planning.

1. INTRODUCTION

The surge in distributed energy resources, mainly renewable generation, coupled with the massive integration of electric vehicles and the rise in household appliances, has altered consumption patterns and heightened the power demand. This scenario calls for an in-depth review of how the electrical system needs to evolve [1]. A long-term transmission network expansion planning (TNEP) needs to be implemented to properly operate the transmission system to support the integration of such resources. The TNEP is a prevalent problem in electrical power systems, where the primary objective is to find the most economical system configuration so proper operation can be guaranteed over a specific planning horizon [2]. Many studies have been done regarding TNEP optimization. In [3], a bi-level evolutionary optimization using a genetic algorithm is used for a coordinated generation and TNEP through an independent system operator standpoint. The work in [4] proposes a teaching learning-based optimization method to solve the TNEP problem for two different transmission systems. In [5], Bender's decomposition approach is implemented to optimize a security-constrained co-planning of transmission line expansion and energy storage to accommodate the penetration of renewable energy. In this work, we intend to use an iterated local search (ILS) algorithm to improve the results obtained from a hybrid-adaptive differential evolution (HyDE) algorithm with different acceptance criteria, such as better, annealing, and restart approaches [6], regarding solution selection in the iteration process, to solve the large-scale TNEP problem, introduced in the "2023 Competition on Evolutionary Computation in the Energy Domain: Operation and Planning Applications" [7]. To the author's knowledge, this sort of implementation using a metaheuristic with a local search method such as HyDE has yet to be seen in the literature regarding TNEP optimization.

2. METHODOLOGY

This section shows the TNEP formulation regarding the objective function and the ILS process used to improve the solutions provided by the HyDE algorithm.

2.1. Transmission System

The optimization problem is labeled as mixed-integer non-linear of combinatorial nature, non-convex, multimodal, and highly complex to optimize for high dimensionality [8]. Eq. (1) depicts the objective function:

$$minimize\ f = \sum_{ij \in \Omega_{Br}} C_{ij} NL_{ij} + \rho \sum_{i \epsilon \Omega_{Bu}} Ls_i \qquad (1)$$

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where Ω_{Br} represents the set of branches in the system going from bus i to bus j and Ω_{Bu} represents the set of buses of the transmission system. The parameter C_{ij} is the cost associated with constructing a new line on the branch ij, and the parameter ρ is the penalty cost for load shedding at bus i. The decision variables are given by NL_{ij} corresponding to the number of lines to be constructed on branch ij and Ls_i represents the load-shedding power at bus i. The objective function is a cost minimization function, subject to several constraints, such as Kirchoff's laws for current and voltage, the transmission capacity limits for the network branches, the bus load shedding maximum bound, the maximum number of lines limit, and the constraint that verifies the NL_{ij} variable must be an integer. The variable NL_{ij} can be fixed at a value, which in this case will be given by the metaheuristic $NL^*_{ij}, \forall ij \in \Omega_{Br}$. This makes the non-linear problem into a linear programming problem, which can be formulated as:

$$minimize\ f' = \rho \sum_{i \epsilon \Omega_{Bu}} Ls_i \tag{2}$$

This objective function minimizes the generation cost of the artificial generators or the load shedding cost penalty, where ρ assumes a substantial value of 1e9 \$/MW. This function is subject to all the previous constraints, except the maximum number of lines and the constraint that dictates that this variable must be integer since we now have this value fixed. A DC optimal power flow then optimizes this equation. The solution returned by this equation is only feasible if it equals 0.

The fixed value of NL^*_{ij} is then added to the previous equation, which gives the objective function to be optimized by the metaheuristic:

$$minimize\ f'' = \sum_{ij \in \Omega_{Br}} C_{ij} N^*_{ij} + \rho \sum_{i \epsilon \Omega_{Bu}} Ls_i \tag{3}$$

The complete mathematical formulation and optimization process can be consulted in [9].

2.2. Iterated local search method

The ILS approach is described in Algorithm 1. The algorithm receives as input the parameters needed to perform the ILS optimization, the case study data regarding the transmission system information, the lower and upper variable bounds, and the initial solution. The initial solution for this particular case is the best solution obtained from the HyDE algorithm (for a description of HyDE, please see [5]), which is then passed as an argument to a hill-climbing function responsible for the local search process, where the best solution obtained is as a local minimum for the iterative process. Iteratively, the algorithm perturbs the solution to avoid getting suck in local optima, which may lead to a worse solution, which is why the local search is applied once again so the new solution space can be locally explored. Finally, an acceptance criterion is chosen to select the best solution for each iteration. We propose three different acceptance criteria based on [10]. The first corresponds to the better acceptance criteria, where only better solutions are accepted with lower fitness values. The second acceptance criteria is the restart approach, where solutions with better fitness are always accepted. Still, after a determined number of iterations without any improvement, the algorithm restarts with the obtained HyDE solution being associated again. The last proposed acceptance criteria represents the annealing method based on the simulated annealing (SA) algorithm. Like in the previous cases, better solutions are still always accepted. However, worse solutions can still be accepted according to an annealing-like cooling schedule, given by an acceptance probability. After the iterative process, the algorithm returns the best-found solution, which for outputs the cost of the best solution is also computed, as well as the fitness vector, with the fitness value for each iteration.

Algorithm 1: Iterated Local Search Method

```
Input: ILS parameters, case study data, variable bounds, initial solution
Output: Best cost value, best solution, fitness vector
s ← get_HyDE_solution
s_best ← hill_climbing(s)
it ← 1
while it < maxIt
  | s_perturbed ← perturb(s_best)
  | s_new ← hill_climbing(s_perturbed)
  | s_best ← acceptance_criteria(s_new)
endwhile
return s_best
```

3. CASE STUDY

This section shows the case study regarding the transmission system information and the parameters utilized for the HyDE-ILS algorithm.

3.1. Transmission System

This study focuses on the north-northeast Brazilian transmission system with 87 buses and 183 branches present in Fig. 1. If generation rescheduling and losses are disregarded, the system's overall generation equals the total demand of 29,748 MW. The current values are multiplied by 1.2 to obtain the original values of generation and demand, resulting in 35,697.60 MW of total demand and generation. Of the 183 branches, only 71 have lines currently in place, while the remaining 112 have no existing lines. It is possible to construct up to 15 new lines on each branch.

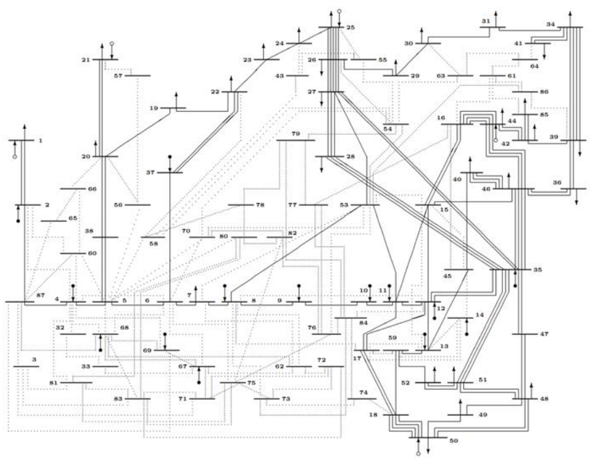

Fig. 1 Line-diagram of the north-northeast Brazilian transmission network (taken from [9]).

3.2. HyDE-ILS parameterization

When it comes to metaheuristic parameterization for the different variations of the HyDE-ILS algorithm, Table 1 shows only the parameters considered for the ILS part of the process because when it comes to the HyDE algorithm, a total number of 10 individuals were considered, with 2,000 iterations corresponding to 20,000 fitness function evaluations. For the mutation and crossover processes, a value for the scaling factor was considered 0.3 and 0.5 for crossover probability. These are only initial values because this algorithm is self-adaptive, which means it will adapt these parameters according to the search process. For all HyDE-ILS variants, a maximum of 50 iterations ($\boldsymbol{it_{max}}$) was considered for the ILS search process due to time constraints, and a step size of 0.1 of the variable value was considered for the hill climbing algorithm. The remaining parameters are shown in Table 1.

Table 1 HyDE-ILS parametrization for all acceptance criteria.

Algorithm	k_{min}	k_{max}	it_{rst}	i_T	α	it_T
HyDE-ILS Better	3	50	-	-	-	-
HyDE-ILS Restart	3	50	$0.2 \cdot it_{max}$	-	-	-
HyDE-ILS Annealing	3	50	-	$0.025 \cdot f(s_{new})$	0.9	10

The $\boldsymbol{k_{min}}$ and $\boldsymbol{k_{max}}$ represent the minimum and maximum limits of the number of variables selected to be perturbed in the perturbation part of the ILS algorithm and is present in all variations. Concerning the HyDE-ILS Restart approach, the number of iterations to restart the algorithm after there is no improvement in the solution is given by $\boldsymbol{it_{rst}}$. Regarding the final acceptance criteria based on SA, the initial temperature ($\boldsymbol{i_T}$) is assumed to be 2.5% of the new solution cost, $\boldsymbol{it_T}$ represents the number of iterations where that algorithm stays at a certain temperature, after these iterations the temperature is decrease according to the parameter α.

4. RESULTS AND DISCUSSION

The optimization results of HyDE-ILS are shown in Table 2 for each acceptance criteria, which are compared to the results obtained from the HyDE algorithm in [9].

Table 2 Average and stand deviation costs, load shedding costs and optimization time for 20 runs.

Algorithm	Avg. Costs ± std ($)	Load Shedding ($)	Avg. Time ± std (min)
HyDE [9]	5.24e6±4.62e5	0	8.48±0.69
HyDE-ILS Better	4.98e6±2.79e5	0	74.55±6.35
HyDE-ILS Restart	4.95e6±4.10e5	0	65.02±16.06
HyDE-ILS Annealing	4.93e6±2.16e5	0	73.44±17.22

In all of the HyDE-ILS results, an improvement is shown regarding the average costs throughout 20 trials. The HyDE-ILS Better achieved a reduction of 4.96% compared to HyDE, while HyDE-ILS Restart achieved a reduction of 5.53%, and HyDE-ILS Annealing achieved a 5.92% cost reduction. All the algorithms presented feasible solutions with the load shedding cost being 0 $. Regarding optimization time, introducing the ILS mechanism to HyDE increased the optimization time by several minutes since, in the local search, we look into all the possible situations where the solution can still be improved, which is very time-consuming. The slowest implemented strategy was the HyDE-ILS Better and the fastest was the HyDE-ILS Restart due to the restart mechanism, which decreases optimization time. The lines constructed in the transmission system, the costs for line construction, and the resultant costs for the construction of the obtained lines are presented in Fig. 2. The solution presented in this figure is for a run of HyDE-ILS Restart, which obtained the lowest costs of all three strategies (4.41e6 $). It is possible to observe that for high construction costs, for the most part, the algorithm decided to construct no lines or a small number of lines on the respective branches. The algorithm convergence for each acceptance criteria is shown in Fig. 3. The HyDE-

ILS Better strategy, as expected, only improved the solution, and the HyDE-ILS Restart with the restart mechanism implemented was also able to improve the initial solution from the HyDE algorithm. In comparison, the HyDE-ILS Annealing strategy, after a few iterations, started to accept worse solutions with no improvement from the initial HyDE solution.

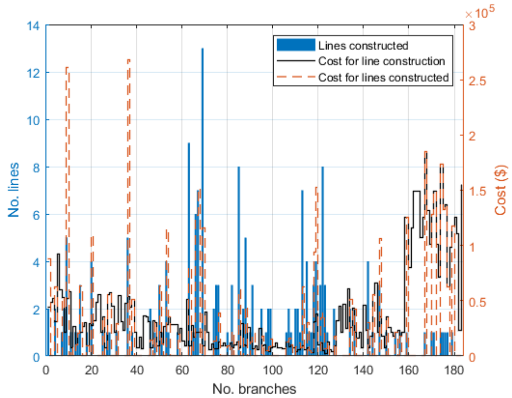

Fig. 2 Lines constructed for each branch and respective costs.

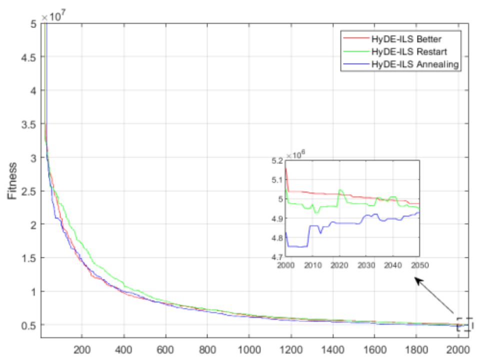

Fig. 3 Average HyDE-ILS convergence curves for each acceptance criteria.

5. CONCLUSIONS

This paper integrated an iterated local search approach into a hybrid-adaptive differential evolution algorithm to improve its results for a TNEP problem. Results showed that this strategy improved the results obtained from only using the HyDE algorithm at a time expense, with HyDE-ILS Annealing showing the lowest average costs from all three strategies. However, when analyzing the convergence curve, it was possible to conclude that HyDE-ILS Annealing only worsened the results with little to no improvement in the perturbation and local search processes, so the other two strategies would be more beneficial. In future work, we intend to apply this strategy to the first three ranked algorithms in the competition to see if there is any improvement in their solutions, which was not considered in this study.

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