Electric Power Systems Research 214 (2023) 108864

Contents lists available at ScienceDirect

Electric Power Systems Research

journal homepage: www.elsevier.com/locate/epsr

Multi-objective transmission expansion planning based on Pareto dominance and neural networks

Felipe L. Miranda [a,*], Leonardo W. Oliveira [a], Edimar J. Oliveira [a], Erivelton G. Nepomuceno [b], Bruno H. Dias [a]

[a] Department of Electrical Energy, Federal University of Juiz de Fora (UFJF), Juiz de Fora, MG, Brazil
[b] Centre for Ocean Energy Research, Deparment of Electronic Engineering, Maynooth University, Ireland

ARTICLE INFO

Keywords:
Transmission expansion planning
Multi-objective optimization
Reliability
Monte Carlo simulation
Neural network

ABSTRACT

This paper presents an algorithm to solve the multi-objective transmission expansion planning (TEP) problem including the investment and reliability criteria. The reliability is considered by using the *Expected energy not supplied* (EENS) index. The main contribution consists on handling the reliability criterion in the optimization process, which tends to provide solutions with better trade-off between the mentioned criteria. For that purpose, a novel probabilistic algorithm called non-dominated Monte Carlo simulation (ND-MCS) is proposed to allow solving the multi-objective TEP problem with suitable computational effort and efficacy even considering the probabilistic feature of reliability in the optimization. In addition, a Support Vector Machine (SVM) network is applied embedded within the ND-MCS. The proposed methodology integrates the Pareto dominance method as a convergence criterion to MCS and a fuzzy criterion to support the decision making. The effectiveness of the proposed approach is tested in three systems, including a practical Brazilian network.

1. Introduction

Transmission expansion planning (TEP) seeks to determine reinforcements to be added to a power system to supply the load demand and meet the operational and reliability constraints at a minimum overall cost. Nevertheless, the TEP problem is a complex optimization task due to the dimensions and features of the power systems. The reliability is an important metric for TEP [1] and the N-1 criterion is commonly used to solve this problem with security constraints. However, in many cases, this criterion can lead to overinvestment [2,3].

On the other hand, although the use of probabilistic methods as the Monte Carlo Simulation (MCS) can be an option for avoiding overinvestment, it may be impracticable due to the high computational effort required [3]. Thus, there are optimization algorithms that obtain expansion plans based on other criteria, as the investment cost, and evaluate the system reliability after the optimization process to select the best option [4]. However, this procedure does not ensure obtaining optimal plans under the reliability criterion.

Therefore, evaluating the reliability together with the steps of a multi-objective optimization algorithm (*a priori*) tends to provide optimal plans even under the reliability standpoint. However, the application of probabilistic frameworks in this case to avoid overinvestments can be prohibitive due to the inherent huge computational requirement. This dilemma is the focus of the present paper that proposes a framework that allows *a priori* probabilistic reliability evaluation with reasonable computational effort. A review of the literature is provided hereinafter.

1.1. The application of reliability indexes in the TEP problem

Metrics derived by the domain experts can be applied for the reliability assessment in power systems. However, the increase of these systems in both size and complexity due to, for instance, new generation and load technologies adds uncertainties that lead to unexpected behavior, which requires more expert models as those based on probability distribution. It can be verified from several works that apply reliability indexes based on probability distribution functions to the TEP problem [4–13], which depend on predictions of transition rates.

1.2. The N-1 criterion in the TEP problem

The N-1 criterion establishes that the transmission system operation must be feasible for the normal condition and for all single outages of

* Corresponding author.
E-mail address: felipe.laure@engenharia.ufjf.br (F.L. Miranda).

https://doi.org/10.1016/j.epsr.2022.108864
Received 7 August 2022; Received in revised form 21 September 2022; Accepted 4 October 2022
Available online 14 October 2022
0378-7796/

Nomenclature

Subscripts and sets

i	System bus
ij	Transmission line
Ω^B	Set of system buses
Ω^C, Ω^E	Sets of candidate and existing lines

Variables

pg_i, rd_i	Active power generation and load shedding at bus i (MW)
θ_{ij}	Angular difference between buses i and j (rad)
f_{ij}^E, f_{ij}^C	Active power flows of existing and candidate lines ij (MW)
Φ_i	Active power flow from bus i (MW)
x_{ij}	Expansion decision (binary variable) for candidate line ij
$EENS$	Expected energy not supplied (MWh)

Parameters

$\overline{pg_i}$	Active power generation capacity at bus i (MW)
d_i	Active load demand at bus i (MW)
b_{ij}, g_{ij}	Susceptance and conductance of line ij (℧)
$\overline{f}_{ij}^E, \overline{f}_{ij}^C$	Active power flow limits of existing and candidate lines ij (MW)
ce_{ij}	Investment cost of candidate line ij ($)
cd	Penalty for load shedding at the planning level ($/MW)
c_{int}	Unit interruption cost ($/MWh)
D_p	Absolute value in each dimension of a MOGWO solution vector
X_p	Position vector of prey in MOGWO
X	Position vector of an individual (candidate plan) of MOGWO
η, n	Population size and number of variables of MOGWO
Ψ	Size of the repository of MOGWO non-dominated solutions
α, β	Grid inflation and leader selection pressure of MOGWO
$nGrid$	Number of grids per hypercube of MOGWO
t, t_{max}	Iteration index and maximum number of iterations of MOGWO

equipment. In practice, a selected and reduced list of contingencies is commonly considered [2], which must be relevant, that is, must have high impact for the system condition. Thus, planning the system to support these events considering that they will necessarily occur (100% probability) can imply overinvestment.

Even in the case of the outages' probabilities are considered in the N-1 criterion for calculating reliability indexes, the plans obtained by probabilistic methods as the MCS can reduce the required investment while maintaining a good reliability level. According to [3], although the N-1 criterion has been adopted by most electric power companies, the best strategy seems to be to ensure this practice only in the most vital system areas, since a high investment would be needed if the whole system had to ensure the N-1 criterion [3].

Despite the aforementioned issue, the N-1 approach has been applied to the TEP problem [5,7-12]. In [5], this is used to obtain the loss of load cost (LOLC) index that is incorporated into the objective function. In [7–12], the minimization of the expected energy not supplied (EENS) is considered in the TEP objective with the aid of the N-1 criterion.

1.3. MCS in the TEP problem

A framework based on Benders decomposition is proposed in [6] to solve the TEP problem considering wind power, where the first-level subproblem makes the investment decision and the second level performs the reliability assessments by using MCS. A similar procedure is done in [13]. In both [6] and [13], a reliability-constrained TEP is formulated, that is, the reliability criterion is considered as a constraint where a minimum pre-established level must be ensured. However, due to the conflicting relationship between investment and reliability, this kind of approach may neglect more reliable solutions, which would be overcame by the development of a multi-objective framework.

1.4. Developments to improve the probabilistic reliability analysis

Due to the required time to assess the system reliability, some works have adopted techniques to make probabilistic methods more efficient [14–18], such as the variance reduction technique [14] and state space pruning [15]. Moreover, classification techniques are developed to reduce the computational effort in the reliability assessment, as artificial neural network (ANN) [16,19], polynomial network [17] and support vector machine (SVM) [18]. However, none of the previous works proposes reliability analysis within the context of the TEP problem.

1.5. Multi-objective frameworks for the TEP problem

Multi-objective approaches can establish a tradeoff between conflicting objectives. In this context, evolutionary algorithms (EA) have been used together with the Pareto method because they can identify multiple attractive solutions [20]. In addition, EA can be quickly built through simple codes even for complex tasks as the TEP problem. A bi-level optimization with genetic algorithm is proposed in [21] for TEP considering N-1 and probable N-2 outages. gray wolf optimization is applied to solve the TEP problem in [5] considering the N-1 criterion. However, none of the found multi-objective frameworks uses MCS to avoid overinvestment in the complex task of obtaining optimal plans under the cost and reliability criteria, due to the MCS computational requirement.

1.6. Paper contributions

The present work proposes a novel efficient approach for the multi-objective TEP that allows considering the reliability criterion in this probabilistic feature together with an optimization process with reasonable computational effort. The TEP problem is formulated as a mixed integer optimization programming based on the investment and reliability criteria, where a new method called Non-dominated Monte Carlo Simulation (ND-MCS) is proposed to efficiently assess the reliability together with the steps of an optimization algorithm, aiming at providing solutions with good trade-off between the criteria.

Moreover, the proposed approach has advantages over deterministic methods due to the proper consideration of the probabilistic feature of the problem at hand, which offers an option to avoid overinvestment in expansion plans that can be alternative to the procedure commonly used in the traditional N-1 practice to define an effective list of events. It can be highlighted that the proposed framework can be applied to obtain the same reliability indexes commonly used in literature [4–13], but with feasible computational requirement even by using MCS in a multi-objective approach.

Candidate plans are obtained by the MOGWO metaheuristic [22] and the SVM is embedded within the ND-MCS. From the final set of non-dominated solutions, a fuzzy decision method [23] is applied to point to a plan based on the planning requirements. Finally, discussions are carried out on the IEEE-RTS 24-bus system and a practical Brazilian network. The tests show the feasibility and effectiveness of the proposed framework in avoiding overinvestment in comparison with the traditional N-1 approach. Therefore, the main contributions are:

- A novel multi-objective TEP approach that allows calculating reliability index by using MCS together with the steps of the proposed optimization algorithm, aiming at providing more reliable plans in relation to methods that assess the reliability only after obtaining a limited set of candidate plans;
- The proposed approach allows properly representing the probabilistic feature of the reliability criterion in the multi-objective TEP problem through MCS, aiming at avoiding overinvestment while optimizing a well-known reliability index commonly used for TEP;
- The proposed framework offers an alternative to the criterion commonly used in the traditional N-1 security analysis that can provide less-cost solutions by considering the probabilities of events in the security criteria decision-making, which is a practical aspect;
- The proposed ND-MCS leads to a more targeted and efficient search in the solution space of the TEP problem.

The remaining sections are outlined as follows: Section 2 presents the background material; Section 3 presents the proposed framework; a tutorial case is presented in Section 4; Section 5 provides the numerical results for the tested systems; and finally, some concluding remarks are given in Section 6.

2. Background material

2.1. Multi-objective TEP formulation

The present work uses the DC load flow model, which is the most adequate way to allow TEP formulation with the incorporation of uncertainty and probabilistic models [1]. The proposal is to determine the number of new lines to be added to the system, aiming at minimizing two expansion costs: (f_1) minimum investment cost; (f_2) minimum reliability index – EENS. The objective functions are modelled in (1) and (2) and subject to the network and planning constraints of (3)-(12).

$$\boldsymbol{Min}(f_1) = \sum_{ij\in\ \Omega^C} \boldsymbol{ce}_{ij}\cdot\boldsymbol{x}_{ij} + \sum_{i\in\ \Omega^B} \boldsymbol{cd}\cdot\boldsymbol{rd}_i \tag{1}$$

$$\boldsymbol{Min}(f_2) = \boldsymbol{EENS} \tag{2}$$

$$\boldsymbol{f}_{ij}^{E} = -\boldsymbol{b}_{ij}\boldsymbol{\theta}_{ij} + \boldsymbol{g}_{ij}\frac{\boldsymbol{\theta}_{ij}^{(\nu)}\cdot\boldsymbol{\theta}_{ij}^{(\nu-1)}}{2}, \forall\ \boldsymbol{ij}\ \in\ \boldsymbol{\Omega}^E \tag{3}$$

$$\boldsymbol{f}_{ij}^{C} = \boldsymbol{x}_{ij}\left(-\boldsymbol{b}_{ij}\boldsymbol{\theta}_{ij} + \boldsymbol{g}_{ij}\frac{\boldsymbol{\theta}_{ij}^{(\nu)}\cdot\boldsymbol{\theta}_{ij}^{(\nu-1)}}{2}\right), \forall\ \boldsymbol{ij}\ \in\ \boldsymbol{\Omega}^C \tag{4}$$

$$\boldsymbol{\Phi}_i = \sum_{ij\ \in\ \Omega_i^E} \boldsymbol{f}_{ij}^{E} + \sum_{ij\ \in\ \Omega_i^C} \boldsymbol{f}_{ij}^{C}, \forall\ \boldsymbol{i}\ \in \boldsymbol{B} \tag{5}$$

$$\boldsymbol{pg}_i - \boldsymbol{\Phi}_i = \boldsymbol{d}_i, \forall\ \boldsymbol{i}\ \in \boldsymbol{B} \tag{6}$$

$$\left|\boldsymbol{f}_{ij}^{E}\right| \le \overline{\boldsymbol{f}}_{ij}^{E},\ \forall\ \boldsymbol{ij}\ \in\ \boldsymbol{\Omega}^E \tag{7}$$

$$\left|\boldsymbol{f}_{ij}^{C}\right| \le \overline{\boldsymbol{f}}_{ij}^{C},\ \forall\ \boldsymbol{ij}\ \in\ \boldsymbol{\Omega}^C \tag{8}$$

$$0 \le \boldsymbol{pg}_i \le \overline{\boldsymbol{pg}_i} \tag{9}$$

$$0 \le \boldsymbol{rd}_i \le \boldsymbol{d}_i \tag{10}$$

$$\boldsymbol{x}_{ij}\ \boldsymbol{binary},\ \forall\ \boldsymbol{ij}\ \in\ \boldsymbol{\Omega}^C \tag{11}$$

$$\boldsymbol{EENS} = \boldsymbol{EPNS} \times\ 8760\ (\boldsymbol{hours}) \tag{12}$$

The objective f_1 minimizes the investment cost in new lines, avoiding the load shedding at the planning level by using a high $\boldsymbol{cd}$ value. The objective f_2, in turn, refers to the reliability criterion. The active power flow in existing and candidate lines is calculated by (3) and (4), respectively. An iterative modified power flow is considered to avoid the nonlinearities caused by the calculation of active losses. The procedure consists on multiplying the variable $\boldsymbol{\theta}_{ij}^{(\nu)}$ of the current iteration $\boldsymbol{\nu}$ by its value from the previous iteration $\boldsymbol{\theta}_{ij}^{(\nu-1)}$, which results in an iterative process. The power balance at bus $\boldsymbol{i}$ related to the Kirchhoff's first law is modelled in (5)-(6). Limits for variables are formulated in (7)-(10). The constraint in (11) models the investment decision variable for every candidate line. The energy interruption index is formulated in (12).

2.2. SVM-based Monte Carlo simulation

The Monte Carlo Simulation is a suitable probabilistic method to assess the reliability of power systems [4]. However, MCS has in general high computational requirement. Thus, classification techniques can be applied to reduce the computational effort in the reliability assessment, as the support vector machine [18], which can open a lack of possibilities for the application of MCS to planning studies.

Therefore, in the present work, the EENS index is obtained by an SVM-based MCS to increase the computational efficiency of the TEP problem. The SVM neural network is trained to distinguish success and failure system states, based on the pattern association between a sampled state and the system variables. The SVM algorithm can be obtained in [18].

It can be highlighted that indexes such as EENS are based on probability distribution functions that depend on transition rates, such as failure rates since the probability of failure is a function of such rates. Although the transition rates can vary, mainly for long-term planning studies, probabilistic approaches must have predictions from historical data to estimate reliability indexes. Thus, in case of an increase in failure rates, for instance, the planning investment may be insufficient in the long-term horizon. On the other hand, in case of failure rates decrease, the planning will be sufficient. Often in the literature, predetermined stochastic data are used in security assessment and planning studies [7,8,10-13], or even data available in test systems, as in [3] and [24].

Despite the mentioned risk, several approaches [4–13] use reliability indexes based on probability distribution functions in the TEP problem. Moreover, methods based on the N-1 criterion that provide reliability indexes [5,7-12] are also subject to the same risk, since these methods depend on probabilities that, in turn, are given by transition rates. However, the N-1 approach can imply overinvestment [2,3] as previously described (Section 1).

2.3. Fuzzy satisfying method

The fuzzy technique is used to choose the final solution in the present work due to its similarity to human reasoning in making choices among options. The membership function in (13) [23], from 0 to 1, is assigned to each objective and its value indicates to what extent a solution satisfies objective f_i. As the problem at hand seeks to minimize the objective functions, the degree is '1' for the minimum objective value (desired) and '0' at the maximum objective value. In other words, the decision maker is fully satisfied in terms of f_i if $\mu_{f_i}(X) = 1$ (reminding that X is a solution plan).

After defining the membership functions, the decision maker must choose the desirable level (μ_{ri}) of every objective, and the suggested solution is obtained by using the 'minmax' decision method of (14) [23] that represents the behavior of a decision maker.

$$\mu_{f_i}(X) = \begin{cases} 0, & f_i(X) > f_i^{max} \\ \dfrac{f_i^{max} - f_i(X)}{f_i^{max} - f_i^{min}}, & f_i^{min} < f_i(X) \le f_i^{max} \\ 1, & f_i(X) \le f_i^{min} \end{cases} \tag{13}$$

$$\min_{X\in\Phi}\left(\max_{i}\left|\mu_{ri}-\mu_{fi}(X)\right|\right) \quad (14)$$

2.4. Multi-objective gray wolf optimizer

The MOGWO algorithm [22] is the multi-objective version of the gray wolf optimizer (GWO) that is inspired by the social hierarchy and hunting behavior of gray wolves in search spaces. In the mathematical model of GWO, the best solution is considered as the alpha (α) individual, according to the social hierarchy of wolves. The second and third best solutions are called beta (β) and delta (δ) wolves, respectively. Details on MOGWO can be found in [22] and its algorithm is provided in the Appendix.

3. Proposed framework

The proposed framework is a multi-objective optimization algorithm for the TEP problem that allows evaluating the system reliability through MCS together with the steps of the algorithm, aiming at providing a good tradeoff between the investment and reliability criteria with reasonable computational requirement. The use of a proper probabilistic method as MCS is proposed to avoid overinvestment [2–4] and SVM is used to enhance the MCS computational efficiency [18]. However, even the original SVM-based MCS [18] spends computational times that make the multi-objective TEP with the reliability assessment together with the optimization steps impractical, in terms of providing multiple plans in suitable times for the planners' analyses.

The fundamental of the proposed framework is that most solutions found by a multi-objective meta-heuristic, as MOGWO, for the TEP problem over the convergence process are dominated (in the concept of the Pareto dominance) under the objective functions (investment and reliability) standpoints. Therefore, the main idea of the proposed approach is to stop the probabilistic evaluation of the reliability index for a given solution when this solution is identified as dominated by another one in the candidate set. Thus, aiming at stopping the SVM-based MCS for dominated solutions and, at the same time, ensuring an accurate estimation for non-dominated solutions, the integration of the Pareto dominance requirements is proposed as part of the convergence process, as follows:

Definition 1. Pareto Dominance

Supposing two solutions, $\boldsymbol{X}$ and $\boldsymbol{Y}$, $\boldsymbol{X}$ dominates $\boldsymbol{Y}$ (denoted as $\boldsymbol{X}\succ\boldsymbol{Y}$) if

$$[f_k(X)\geq f_k(Y)]\ \forall k\in[1,2] \quad (15)$$

Definition 2. Pareto Optimality

A solution X is called Pareto-optimal if

$$\nexists Y \mid f_k(Y)\succ f_k(X)\ \forall k\in[1,2] \quad (16)$$

In the previous equations, $k\in[1,2]$ because there are two objective functions: f_1 and f_2. A set containing the Pareto optimal solutions is called Pareto optimal front. Thus, the present paper proposes the Non-dominated MCS (ND-MCS) that is based on adding the Pareto dominance criterion to the SVM-based MCS convergence criteria. For that purpose, a dominance test function F_{DOM} is evaluated together with the test functions of the system performance indexes (LOLP, EPNS). Function F_{DOM}, formulated in (17), is updated every iteration and accurately estimates the probability that a solution will be dominated by another one in the candidate set. The expected value of F_{DOM} for a solution X is given by (18).

$$F_{DOM}(X)=\begin{cases}0, & if\ X\ is\ non-dominated\\ 1, & if\ X\ is\ dominated\end{cases} \quad (17)$$

$$\widetilde{E}(F_{DOM}(X))=\frac{1}{NS(X)}\sum_{s=1}^{NS(X)}F_{DOM,s}(X) \quad (18)$$

Where $\boldsymbol{F_{DOM,s}(X)}$ is the estimated value of $\boldsymbol{F_{DOM}(X)}$ for state $\boldsymbol{s}$ and $\boldsymbol{NS(X)}$ is the number of sampled system states $\boldsymbol{s}$. Note that the EENS index is obtained similarly to (18) by using $\boldsymbol{F_{EENS}}$ (EENS test function) instead of $\boldsymbol{F_{DOM}}$ [25]. The uncertainty over the estimate is given by the variance of the test function $\boldsymbol{F_{DOM}}$ ($\boldsymbol{V(X)}$) and the variation coefficient ($\boldsymbol{\beta_{DOM}(X)}$) [25] as:

$$\boldsymbol{V(X)}=\frac{\boldsymbol{V(F_{DOM}(X))}}{\boldsymbol{NS(X)}} \quad (19)$$

$$\boldsymbol{\beta_{DOM}(X)}=\frac{\sqrt{\boldsymbol{V(\widetilde{E}(F_{DOM}(X)))}}}{\boldsymbol{\widetilde{E}(F_{DOM}(X))}}\times\ 100\% \quad (20)$$

If the $\boldsymbol{\beta_{DOM}(X)}$ criterion is not reached, that is, if the solution is considered as not dominated, the ND-MCS converges based on the traditional criteria related to the system performance indexes ($\boldsymbol{\beta_{LOLP}}$, $\boldsymbol{\beta_{EPNS}}$). Thus, only non-dominated solutions that integrate the Pareto front have their reliability indexes estimated, avoiding unnecessary analyses by MCS.

3.1. Proposed algorithm

The proposed algorithm is presented in Fig. 1 and explained next. The ND-MCS is highlighted in the dashed line. The maximum number of MOGWO iterations is the convergence criterion. In addition to increasing the computational efficiency in evaluating the EENS index, the ND-MCS search strategy even tends to improve the quality of the final solutions because it allows filtering the non-dominated ones and, therefore, allows a more targeted and efficient search in the solution space.

1) Input the system data (deterministic and stochastic parameters).
2) Generate a first random population of gray wolves. Initialize the MOGWO parameters.
3) For all individuals in the population (candidate plans), calculate f_1.

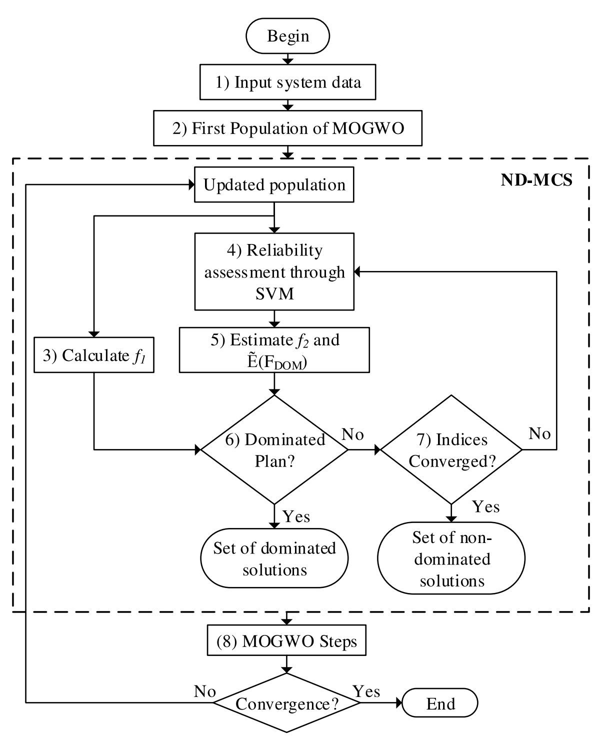


Fig. 1. Flowchart of proposed framework.

4) Initialize the reliability assessment through the SVM-based MCS for all individuals.
5) Update the estimate for f_2 and the dominance probability for every solution ($\widetilde{\boldsymbol{E}}(\boldsymbol{F_{DOM}})$).
6) Based on Steps 3) and 5), verify the dominance criterion. If a solution is dominated, end the ND-MCS and go to Step 8). Otherwise, go to Step 7).
7) If the EENS index does not converge, return to Step 4); otherwise, store the plan in the set of non-dominated solutions and go to Step 8).
8) Apply the MOGWO steps described in the Appendix. If the maximum number of iterations is not reached, return to Step 3) to evaluate the fitness of every updated gray wolf. Otherwise, end MOGWO and plot the Pareto front.

After the convergence of the proposed algorithm of Fig. 1 and determining the final set of non-dominated solutions, a decision must be made by the planner. This decision making must represent a trade-off between different objectives based on the planner's preferences [23]. According to the fuzzy method of Section 2.3, the investment criterion is fully satisfied for a given plan $\boldsymbol{X}$ if $\boldsymbol{\mu}_{f_1}(\boldsymbol{X}) = 1$, that is, the investment of $\boldsymbol{X}$ is the minimal from the non-dominated Pareto front in this case, which implies the maximum EENS and $\boldsymbol{\mu}_{f_2}(\boldsymbol{X}) = 0$. On the other hand, the investment and EENS are the highest and lowest from the Pareto front, respectively, for a solution $\boldsymbol{X}$ that has $\boldsymbol{\mu}_{f_1}(\boldsymbol{X}) = 0$ and $\boldsymbol{\mu}_{f_2}(\boldsymbol{X}) = 1$.

Finally, it should be highlighted that the proposed framework does not necessarily provide the optimum expansion plan for the TEP problem, but high-quality plans within acceptable CPU time.

4. Tutorial case: Garver test system

This section presents a tutorial case to exemplify the application of the proposed approach to the well-known Garver 6-bus test system. The data of the existing and candidate lines of the system can be found in [26]. The failure rate (λ) and repair time ($\boldsymbol{MTTR}$) of the transmission lines are 0.0781/mile.year and 10 h, respectively, as in [3]. As in [3], the EENS index is obtained for the peak load that is available in [26].

The MOWGO parameters are [22]: t_{max}= 100; η = 25; Ψ = 50; α = 0.1; β = 4; $nGrid$ = 10. The algorithm was implemented in MATLAB®, in a 2.2 GHz Intel® Core™ i5–5200. The CPLEX 12.9.0 (Copyright© IBM Corp.) optimization package was used to solve the DC—OPF to verify the system constraints for the MCS samples, by using the Primal-Dual Interior Point method.

Table 1 presents the results found in literature for single-objective studies focused on investment cost, without any security criteria and considering peak load and power loss. This table provides the reinforcements – 'number of added lines' (branch) – and the investment cost f_1. Notation '3′(4–6), for instance, means the investment in three lines at branch (4–6). Table 2 presents the non-dominated solutions of the Pareto front obtained by the proposed framework.

Note that the plans of Table 1 are among those of the Pareto front obtained by the proposed algorithm - P1 and P2 in Table 2. This proves that the proposed approach can find good quality solutions, including those already found in the literature for only minimum investment cost. In relation to the non-dominance concept, solution P1 does not dominate P2, since although P1 has f_1 smaller than P2, P1 has the greatest f_2 value. This means that P1 is better than P2 in terms of investment, but P2 has the best reliability. The same reasoning can be extended to the other Pareto front solutions. The overall run time was 10 min.

Table 1
Results from literature for the Garver system.

Reference	Reinforcements	f_1 (10^6 US$)
[27]	'3′(4–6), '1′(2–3), '1′(3–5)	130.00
[28]	'2′(4–6), '2′(2–6), '1′(3–5)	140.00

Table 2
Proposed non-dominated solutions (Pareto front) for the Garver system.

Plan	Reinforcements	f_1 (10^6 US$)	f_2 (MWh)
P1	'3′(4–6), '1′(2–3), '1′(3–5)	130.00	5126.0
P2	'2′(4–6), '2′(2–6), '1′(3–5)	140.00	4176.3
P3	'3′(4–6), '1′(2–3), '2′(3–5)	150.00	3706.6
P4	'3′(4–6), '1′(2–6), '2′(3–5)	160.00	0

The solutions of Table 2 show the conflicting relation between the investment and reliability index. This means that the increase of the investment in transmission lines decreases the EENS due to improvement in the system security [29]. From the portfolio of non-dominated solutions, the decision-making applies the fuzzy satisfying technique [29], by setting the minimum and maximum objective functions at the respective limits from Table 2, that is: f_1^{min} = 130.00 and f_1^{max} = 160.00; f_2^{min} = 0 and f_2^{max} = 5126.00. Other limits can be defined for f_1 and f_2 according to the planning requirements. In relation to the references μ_{r1} and μ_{r2} that also depend on the planning criteria, the following cases were evaluated: $\mu_{r1} = \mu_{r2} = 0.8$; $\mu_{r1} = 0.8$ and $\mu_{r2} = 0.6$; $\mu_{r1} = 0.6$ and $\mu_{r2} = 0.8$, and the selected plan was P2 in every case.

In order to assess the statistical meaningfulness of the obtained result, 50 runs of the proposed algorithm were done for $\mu_{r1} = \mu_{r2} = 0.8$ and the results are given in Table 3. It can be observed that P2 is obtained in 94% of the runs, which shows that the proposed study has statistical relevance. Fig. 2 illustrates the summary statistics of Table 3 by using the toolbox boxplot of MATLAB®, which shows the values obtained for f_1 and f_2 in most of the runs, represented by horizontal lines, as well as the other values represented by crosses.

5. Results and discussion

The proposed framework is applied for two other systems: 24-bus IEEE-RTS and Brazilian Southern systems. As in [3], the peak load is considered to estimate the EENS index and the MOGWO parameters are the same as the tutorial case. Every candidate branch can receive a maximum of three lines. For the fuzzy decision-making criterion, the minimax satisfying method is used and $\mu_{r1} = \mu_{r2} = 0.8$. To assess the proposed approach, the following analyses are performed:

i) $\text{MOGWO}_{\text{ND}-\text{MCS}}$ – Consists on the proposed framework where the novel ND-MCS approach is applied to acquire the EENS index;
ii) $\text{MOGWO}_{\text{MCS}}$ – Consists on the application of the MOGWO algorithm associated with the original or crude MCS to obtain the EENS index, that is, in this analysis the MCS is used without the improvement proposed in the present work;
iii) $\text{MOGWO}_{\text{N-1}}$ – Consists on the application of the MOGWO algorithm associated with the N-1 criterion to calculate the EENS index;
iv) $\text{MOCSA}_{\text{N-1}}$ – Consists of the method proposed in [30] that applies the multi-objective algorithm named crow search (MOCSA), associated with the N-1 criterion to obtain the EENS index;
v) $\text{MOGWO}_{\text{ND}-\text{MCS5}}$ – Consists on the proposed framework, as in analysis i), but with an increase of 5% in the failure rate of all lines.

It can be highlighted that analyses ii), iii) and iv) seek to provide a basis for comparison to the proposed $\text{MOGWO}_{\text{ND}-\text{MCS}}$ approach.

Table 3
Statistical analysis.

No. of occurrences	Plan	f_1 (10^6 US$)	f_2 (MWh)
47 (94%)	P2	140.00	4176.3
1 (2%)	P3	150.00	3706.6
2 (4%)	P4	160.00	0

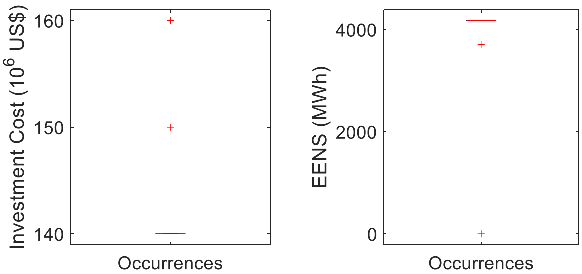


Fig. 2. Summary statistics.

Analysis v), in turn, seeks to evaluate the impact of a variation in the failure rates on the proposed final plan. The N-1 criterion considers the single outage of each transmission line in the system.

5.1. IEEE-RTS 24-bus system

The IEEE-RTS system has 24 buses and 34 branches containing existing and candidate lines. The data on lines' parameters, system topology and nodal loads can be found in [24]. The peak load is 8550 MW and the maximum generation capacity is 10,215 MW. The failure rate and repair time of the transmission lines are also in [24]. The system is commonly modified in the literature by doubling its demand and generation capacity to make it less reliable and increase the TEP difficulty [31]. The best single-objective solution from the literature [30,32] focused on only investment has a cost of US$ 152.00 × 10^6. Fig. 3.a) and 3.b) show the set of non-dominated plans from the proposed MOGWO$_{ND-MCS}$ algorithm, together with those from the previously defined MOGWO$_{MCS}$ and MOCSA$_{N\text{-}1}$. Table 4 presents the final plans chosen after the application of the fuzzy criterion to the MOGWO$_{ND-MCS}$ and MOGWO$_{MCS}$ Pareto fronts.

From Fig. 3.a), it can be observed that the Pareto front from MOGWO$_{ND-MCS}$ is very close to the MOGWO$_{MCS}$ front, which shows that the proposed ND-MCS approach can maintain the features of the original or crude MCS, but with a substantial reduction in the computational time. This advantage can be ascertained in Table 4 by the reduction of 82% from the proposed MOGWO$_{ND-MCS}$ in relation to the MOGWO$_{MCS}$ solution. In addition, Fig. 3.a) shows that the points of the MOGWO$_{ND-MCS}$ front tend to be below those from MOGWO$_{MCS}$, which means that the quality of the proposed solutions tends to be better, since the objective is to minimize both objective functions. This occurs because the proposed ND-MCS leads to a more targeted and efficient search in the TEP solution space, due to the filtering of non-dominated points over the optimization steps.

The previous behavior can also be verified in Fig. 3.b), that is, the proposed Pareto front is better (below) the MOCSA$_{N\text{-}1}$ front, which can also indicate that the ND-MCS approach can avoid overinvestments, due to the lower investment cost of the MOGWO$_{ND-MCS}$ points in the figure, in relation to the N-1 criterion.

About the planning criteria, Table 4 shows that the proposed MOGWO$_{ND-MCS}$ increases the investment cost in US$ 3.00 × 10^6 (1.08%) and decreases EENS in 1823.10 MWh (16.47%). These solutions differ by only one line - '1′(1–2) - that is added in the proposed approach, increasing the investment and improving the reliability. Table 5: Comparison among the proposed analyses, IEEE 24-bus system summarizes the results for the planning objectives in all the previously defined analyses. For each objective, the percentual of 100% was addressed to the largest value among the analyses.

In terms of the investment cost (f_1), although the MOGWO$_{MCS}$ analysis leads to the best value, the difference from the proposed MOGWO$_{ND-MCS}$ plan is of 1.08%, whereas the proposed plan has an EENS better than the MOGWO$_{MCS}$ analysis, with a difference of 16.47%, as previously stated. In terms of reliability (f_2), in turn, the best EENS is from the MOGWO$_{N\text{-}1}$ analysis. However, this solution has the highest investment cost, with a difference of around 14.5% in relation to the proposed MCS-based framework, which indicates that the N-1 criterion can imply in overinvestment. Moreover, these results point out that the proposed framework can obtain a better trade-off between the planning criteria.

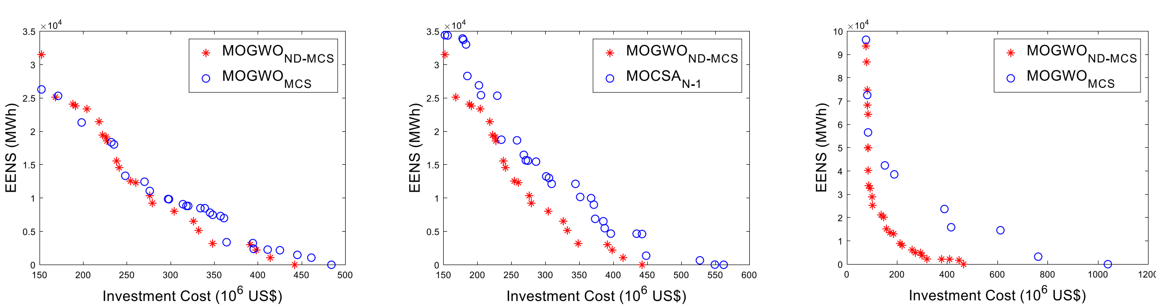
Finally, Table 5: Comparison among the proposed analyses, IEEE 24-bus system shows also the MOGWO$_{ND-MCS5}$ solution, which considers an increase of 5% in all failure rates. It can be verified that even under this increase, the investment cost of the MOGWO$_{ND-MCS5}$ plan is lower than the MOGWO$_{N\text{-}1}$ cost from the N-1 criterion. This analysis shows that although the transition rates' prediction has impact on the final plan, the N-1 practice tends to be more conservative in terms of reinforcements and thus can lead to overinvestment, as previously pointed out by [2–4].

Table 6 presents the 'R' and 'L' solutions for the MOGWO$_{ND-MCS}$, MOGWO$_{N\text{-}1}$, MOCSA$_{N\text{-}1}$ and MOGWO$_{ND-MCS5}$ analyses, where 'R' is the extreme solution having the lowest f_1 and highest f_2 found in each analysis, and 'L' has the highest f_1 and lowest f_2. The 'R' solution is the same for all analyses and corresponds to the plan found in the literature focused on only investment cost (single-objective) [30,32].

On the other hand, all the 'L'-solutions have the EENS index equal to zero. Thus, the investment cost must be used in this case to define the dominance among these plans. The conclusion is that the proposed 'L'-solution ($L_{MOGWO_{ND-MCS}}$) dominates the others 'L'-solutions for having the smallest investment cost (f_1). As the 'R'-solutions are all the same, it can be concluded that the proposed MOGWO$_{ND-MCS}$ Pareto front dominates the Pareto fronts from the other analyses, showing that the proposed framework is a potential option to support the TEP effort by providing good quality alternative plans.

5.2. The Brazilian Southern system

The Brazilian Southern system (BSS) has data, including grid topology, lines' parameters, nodal loads, existing and candidate lines, available in [33]. For the reliability analysis, practical and still current



a): MOGWO$_{ND-MCS}$ × MOGWO$_{MCS}$ b): MOGWO$_{ND-MCS}$ × MOCSA$_{N\text{-}1}$ c): Solutions for the BSS system

Fig. 3. a): MOGWO$_{ND-MCS}$ × MOGWO$_{MCS}$, 3.b): MOGWO$_{ND-MCS}$ × MOCSA$_{N\text{-}1}$, c): Solutions for the BSS system.

Table 4
Final plans for the IEEE 24-bus system.

Analysis	Reinforcements	f_1 (10^6 US$)	f_2 (MWh)	CPU time
Proposed $MOGWO_{ND\_MCS}$	'1′(1–2), '1′(1–5), '1′(3–24), '2′(6–10), '2′(7–8), '1′(10–12), '1′(14–16), '1′(16–17)	279.00	9240.90	2 h. 10 min. (18%)
$MOGWO_{MCS}$	'1′(1–5), '1′(3–24), '2′(6–10), '2′(7–8), '1′(10–12), '1′(14–16), '1′(16–17)	276.00	11,064.00	12 h. 15 min. (100%)

Table 5
Comparison among the proposed analyses, IEEE 24-bus system.

Analysis	f_1 (10^6 US$)	f_2 (MWh)
Proposed $MOGWO_{ND-MCS}$	279.00 (85.58%)	9240.90 (59.73%)
$MOGWO_{MCS}$	276.00 (84.66%)	11,064.00 (71.52%)
$MOGWO_{N\text{-}1}$	326.00 (100%)	5673.9 (36.67%)
$MOGWO_{ND-MCS5}$	306.00 (93.86%)	9294.50 (60.08%)
$MOCSA_{N\text{-}1}$	286.00 (87.73%)	15,470.00 (100%)

Table 6
R and L solutions for the 24-bus system.

Analysis	Reinforcements	f_1 (10^6 US$)	f_2 (MWh)
$R_{MOGWO_{N-1}}$, $R_{MOCSA_{N-1}}$, $R_{MOGWO_{ND-MCS}}$, $R_{MOGWO_{ND-MCS5}}$	'1′(6–10), '2′(7–8), '1′(10–12), '1′(14–16)	152.00	31,264.00
$L_{MOGWO_{N-1}}$	'1′(1–2), '1′(1–5), '1′(2–6),'1'(3–24), '1′(4–9), '3′(6–10), '2′(7–8), '1′(9–11), '1′(10–12), '1′(11–13), '1′(14–16), '1′(15–24), '1′(16–17)	560.00	0
$L_{MOGWO_{ND-MCS}}$	'1′(3–24), '2′(6–10), '2′(7–8), '1′(10–11), '1′(10–12), '1′(11–13), '1′(14–16), '1′(15–24), '1′(16–17)	442.0	0
$L_{MOCSA_{N-1}}$	'1′(1–2), '1′(1–5), '1′(2–4),'1'(3–24), '2′(6–10), '2′(7–8), '1′(9–12), '1′(10–12), '1′(12–13), '1′(14–16), '1′(15–21), '1′(15–24), '1′(20–23)	562.00	0
$L_{MOGWO_{ND-MCS5}}$	'1′(1–2), '1′(1–5), '1′(3–9),'1'(3–24), '2′(6–10), '2′(7–8), '1′(9–11), '1′(10–11), '1′(10–12), '1′(11–13), '1′(14–16), '1′(16–17), '1′(17–18), '1′(20–23)	526.00	0

probabilistic data from the Brazilian National System Operator (ONS) are used for transmission lines ($\lambda = 0.02542$/miles.year and $MTTR = 2.958$ h for 138 kV lines; $\lambda = 0.00707$/miles.year and $MTTR = 1.521$ h for 500 kV lines). According to the literature, the best single-objective solution for BSS focused on investment has cost of US\$ 75.90 $\times 10^6$ [31].

Fig. 3.c) presents the obtained non-dominated solutions, where it can be observed that the proposed $MOGWO_{ND-MCS}$ Pareto front has better behavior than the $MOGWO_{MCS}$ front, that is, the proposed front is below the other in the figure. Therefore, the proposed non-dominated set has cheaper and more reliable plans in relation to the other set used for comparison. As in the previous systems, the non-dominated plans from the proposed approach comprise the single-objective solution from the literature [31].

Table 7 shows the final plans obtained by the proposed algorithm and the fuzzy decision-making criterion. Some branches are in all analysis - (18–20), (20–23), (20–21), (42–43), (46–6) and (5–6) - indicating their relevance. The investment costs from [27] and [31] considering the N-1 criterion are US\$ 153.10 $\times 10^6$ and US\$ 189.50 $\times 10^6$, respectively. Thus, the proposed $MOGWO_{ND-MCS}$ algorithm achieves a smaller cost, US\$ 146.31 $\times 10^6$, reinforcing that the improved MCS-based approach can avoid overinvestment by a proper representation of the probabilistic feature of equipment' outages.

From Table 7, the $MOGWO_{ND-MCS}$ solution is cheaper than the

Table 7
Final plans for the BSS system.

Analysis	Reinforcements	f_1 (10^6 US $)	f_2 (MWh)	CPU time
$MOGWO_{ND-MCS}$	'1′(12–14), '1′(18–20), '1′(19–21), '1′(14–22), '1′(20–23), '1′(24–34), '2′(20–21), '2′(42–43), '1′(46–6), '1′(29–30), '2′(5–6)	146.31	20,173.00	2 h. 33 min. (31%)
$MOGWO_{MCS}$	'1′(2–5), '1′(9–14), '1′(12–14), '1′(13–18), '1′(18–20), '1′(14–22), '1′(20–23), '1′(36–37), '1′(34–35), '1′(37–39), '1′(37–42), '1′(39–42), '2′(38–42), '1′(32–43), '1′(19–32), '1′(46–16), '3′(20–21), '2′(42–43), '1′(46–6), '1′(16–32), '1′(28–43), '1′(41–43), '1′(29–30), '1′(2–3), '3′(5–6)	388.42	23,692.00	6 h. 39 min. (100%)

$MOGWO_{MCS}$ plan by 62.33% (f_1). In addition, the $MOGWO_{ND-MCS}$ plan has the EENS value (f_2) lower than $MOGWO_{MCS}$ by 14.85%. Finally, The CPU time decreases significantly from $MOGWO_{MCS}$ to $MOGWO_{ND-MCS}$ (69%), which proves the effectiveness and computational efficiency of the proposed framework.

Still on the computational requirement, it can be highlighted that the proposed framework can be a potential tool to be applied to large-scale systems, which is supported by the fact that the MCS efficiency depends more on the equipment availability than the grid size, according to [34]. In particular, the more reliable the system, the higher is the MCS effort [34]. Thus, as the proposed framework is based on an efficient MCS procedure (ND-MCS), the computational requirement will depend more on the system reliability than the grid size, which will be explored in future developments.

Finally, it can be pointed out that in practical cases, the decision maker should run a detailed analysis with different satisfying methods to find the best trade-off among the non-dominated solutions. The proposed framework allows the planner to adopt criteria more flexible to meet the stakeholders' exigences. For instance, if the chosen solution does not satisfy dynamic constraints, short circuit levels or any condition that leaves the system to load shedding, the planner can simply change to other plans in the neighborhood of the first one having similar performances with respect to the objectives [29].

6. Conclusions

This paper proposed a novel approach to allow solving the TEP problem with the reliability criterion considered in this probabilistic feature and *a priori*, i.e., over the optimization procedure. The advantage is that the final obtained plans can represent a better trade-off between the reliability and economic criteria, since the optimization is carried out also under the reliability standpoint over the steps of the proposed algorithm. Another advantage is that it is possible to avoid over-investment by considering the probabilistic feature of the equipment' outages. The results obtained by the introduced case studies showed this expected benefit. It can be highlighted that the major challenge to consider the reliability criterion *a priori* in a probabilistic manner is the high and prohibitive computational effort mainly for practical electrical transmission systems. In this sense, the proposed ND-MCS probabilistic framework can meet the computational requirement due to its efficiency in obtaining the reliability index over the optimization process, as shown in the case studies. In addition, the proposed algorithm allows a better search in the solution space due to its capacity of identifying non-dominated and, thus, attractive candidate solutions over the optimization steps. As a future development, it can be suggested the investigation of how the prediction of transition rates, as failure and repair rates, impacts on the planning problem. Another suggestion is to investigate and quantify how the system size and equipment availability impact on the computational requirement to solve the problem through the improved MCS-based approach.

7. Credit author statement

Felipe L. Miranda: Methodology, Software, Validation, Writing Leonardo W. Oliveira: Investigation, Writing, Supervision Edimar J. Oliveira: Software, Supervision Erivelton G. Nepomuceno: Conceptualization, Supervision Bruno H. Dias: Reviewing and Editing

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgements

The authors would like to thank CAPES, FAPEMIG, INERGE and the National Council for Scientific and Technological Development – CNPq for supporting this research.

Appendix

The pseudo-code of the MOGWO algorithm to solve the proposed multi-objective TEP problem is given hereinafter [22]:

begin
Initialize gray wolf population $X_i (i = 1, 2, \ldots, \eta)$
Initialize a, A and C
Compute objective functions f_1 and f_2 of each gray wolf
Find non-dominated solutions based on f_1 and f_2, and initialize the repository with them
$(X_\alpha, X_\beta, X_\delta) \leftarrow$ select leaders from repository
$t \leftarrow 1$
while $t < t_{max}$ do
for each gray wolf do
Update its position by Eq. (13)
Update a, A and C
Compute objective functions f_1 and f_2 of each gray wolf
Find non-dominated solutions based on f_1 and f_2, and initialize the repository with them
if repository is full then
Run the grid mechanism to remove one of the current members and add the new solutions to the repository
if any of the new solutions added to the repository is located outside the hypercubes then
Update the grids to cover new solutions
$(X_\alpha, X_\beta, X_\delta) \leftarrow$ select leaders from repository
$t \leftarrow +1$
return repository

References

[1] P.V. Gomes, J.T. Saraiva, State-of-the-art of transmission expansion planning: a survey from restructuring to renewable and distributed electricity markets, Int. J. Electric. Power Energy Syst. 111 (Oct. 01, 2019) 411–424, https://doi.org/10.1016/j.ijepes.2019.04.035.

[2] A.N. de Paula, E.J. de Oliveira, L.W. de Oliveira, L.M. Honório, Robust static transmission expansion planning considering contingency and wind power generation, J. Control Automat. Electric. Syst. 31 (2) (2020) 461–470, https://doi.org/10.1007/s40313-019-00556-w. Apr.

[3] A.M. Leite da Silva, L.S. Rezende, L.A.F. Manso, G.J. Anders, Transmission expansion planning: a discussion on reliability and 'N-1' security criteria, in: 2010 IEEE 11th International Conference on Probabilistic Methods Applied to Power Systems, PMAPS, 2010, pp. 244–251, https://doi.org/10.1109/PMAPS.2010.5528652, 2010.

[4] A.M. Leite Da Silva, L.S. Rezende, L.A. da Fonseca Manso, L.C. de Resende, Reliability worth applied to transmission expansion planning based on ant colony system, Int. J. Electric. Power Energy Syst. 32 (10) (2010) 1077–1084, https://doi.org/10.1016/j.ijepes.2010.06.003.

[5] A.A. Ghadimi, M. Amani, M. Bayat, S. Ahmadi, M.R. Miveh, F. Jurado, Stochastic transmission expansion planning in the presence of wind farms considering reliability and N-1 contingency using grey wolf optimization technique, Electric. Eng. 104 (2) (2022) 727–740, https://doi.org/10.1007/s00202-021-01339-w. Apr.

[6] L.C. da Costa, F.S. Thome, J.D. Garcia, M.V.F. Pereira, Reliability-constrained power system expansion planning: a stochastic risk-averse optimization approach, IEEE Trans. Power Syst. 36 (1) (2021) 97–106, https://doi.org/10.1109/TPWRS.2020.3007974. Jan.

[7] F.S. Gazijahani, S.N. Ravadanegh, J. Salehi, Stochastic multi-objective model for optimal energy exchange optimization of networked microgrids with presence of renewable generation under risk-based strategies, ISA Trans. 73 (2018) 100–111, https://doi.org/10.1016/j.isatra.2017.12.004. Feb.

[8] P. Praveen, S. Ray, J. Dasl, A. Bhattacharya, Multi-objective power system expansion planning with renewable intermittency and considering reliability, in: 7th IEEE International Conference on Computation of Power, Energy, Information and Communication, ICCPEIC, 2018, pp. 424–429, https://doi.org/10.1109/ICCPEIC.2018.8525214, 2018.

[9] F. Ugranli, E. Karatepe, Multi-objective transmission expansion planning considering minimization of curtailed wind energy, Int. J. Electric. Power Energy Syst. 65 (2015) 348–356, https://doi.org/10.1016/j.ijepes.2014.10.031.

[10] M. Kazemi, M.R. Ansari, An integrated transmission expansion planning and battery storage systems placement - a security and reliability perspective, Int. J. Electric. Power Energy Syst. 134 (Jan. 2022), https://doi.org/10.1016/j.ijepes.2021.107329.

[11] H. Hamidpour, S. Pirouzi, S. Safaee, M. Norouzi, M. Lehtonen, Multi-objective resilient-constrained generation and transmission expansion planning against natural disasters, Int. J. Electric. Power Energy Syst. 132 (2021), https://doi.org/10.1016/j.ijepes.2021.107193. Nov.

[12] A. Davoodi, A.Reza Abbasi, S. Nejatian, Multi-objective dynamic generation and transmission expansion planning considering capacitor bank allocation and demand response program constrained to flexible-securable clean energy, Sustain. Energy Technol. Assess. 47 (2021), https://doi.org/10.1016/j.seta.2021.101469. Oct.
[13] A.N. de Paula, E.J. de Oliveira, L.W. Oliveira, C.A. Moraes, Reliability-constrained dynamic transmission expansion planning considering wind power generation, Electric. Eng. 102 (4) (2020) 2583–2593, https://doi.org/10.1007/s00202-020-01054-y. Dec.
[14] B. Zhaohong, W. Xifan, Studies on variance reduction technique of Monte Carlo simulation in composite system reliability evaluation, Electric Power Syst. Res. 63 (1) (2002) 59–64, https://doi.org/10.1016/S0378-7796(02)00089-5.
[15] C. Singh, J. Mitra, Composite system reliability evaluation using state space pruning, IEEE Power Eng. Rev. 17 (2) (1997) 73–74.
[16] X. Luo, C. Singh, A.D. Patton, Power system reliability evaluation using learning vector quantization and Monte Carlo simulation, Electric Power Syst. Res. 66 (2) (2003) 163–169, https://doi.org/10.1016/S0378-7796(03)00025-7.
[17] A.M. Leite da Silva, L.C. de Resende, L.A. da Fonseca Manso, V. Miranda, Composite reliability assessment based on Monte Carlo simulation and artificial neural networks, IEEE Trans. Power Syst. 22 (3) (2007) 1202–1209, https://doi.org/10.1109/TPWRS.2007.901302.
[18] C.S.N. Piandoriya, P. Jirutitijaroen, D. Srinivasan, Composite reliability evaluation using monte carlo simulation and least squares support vector classifier, IEEE Trans. Power Syst. 26 (4) (2011) 2483–2490 [Online]. Available, http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=5729852.
[19] J.T.S.V.M.L.M.V.G. Pinto, Generation/transmission power system reliability evaluation by Monte-Carlo simulation assuming a fuzzy load description, IEEE Trans. Power Syst. 11 (2) (1996) 690–695.
[20] Z. Michalewicz, D.B. Fogel, How to Solve it: Modern Heuristics, Springer Science & Business Media, 2013.
[21] N. Gupta, M. Khosravy, N. Patel, T. Senjyu, A Bi-level evolutionary optimization for coordinated transmission expansion planning, IEEE Access 6 (2018) 48455–48477, https://doi.org/10.1109/ACCESS.2018.2867954. Aug.
[22] S. Mirjalili, S. Saremi, S.M. Mirjalili, L.D.S. Coelho, Multi-objective grey wolf optimizer: a novel algorithm for multi-criterion optimization, Expert Syst. Appl. 47 (2016) 106–119, https://doi.org/10.1016/j.eswa.2015.10.039.
[23] R. Gholizadeh-Roshanagh, K. Zare, M. Marzband, An A-posteriori multi-objective optimization method for MILP-based distribution expansion planning, IEEE Access 8 (2020) 60279–60292, https://doi.org/10.1109/ACCESS.2020.2981943.
[24] P.M. Subcommittee, IEEE reliability test system, IEEE Trans. Power Apparatus Syst. 98 (6) (1979) 2047–2054. PAS-.
[25] M.V.F. Pereira, N.J. Balu, S. Member, A. Objectives, P. System, Composite Generation /Transmission Reliability Evaluation, Proc. IEEE 80 (4) (1992) 470–491.
[26] L.L. Garver, Transmission network planning using linear programming, IEEE Trans. Apparatus Syst. 89 (7) (1970) 1688–1697, https://doi.org/10.1109/MPER.1985.5528872. PAS-.
[27] E.J. de Oliveira, C.A. Moraes, L.W. Oliveira, L.M. Honório, R.P.B. Poubel, Efficient hybrid algorithm for transmission expansion planning, Electric. Eng. 100 (4) (2018) 2765–2777, https://doi.org/10.1007/s00202-018-0744-2.
[28] N. Alguacil, A.L. Motto, A.J. Conejo, Transmission expansion planning: a Mixed-Integer LP approach, IEEE Trans. Power Syst. 18 (3) (2003) 1070–1077, https://doi.org/10.1201/9780429455094-16.
[29] M.S.P. Maghouli, S.H. Hosseini, M.O. Buygi, A multi-objective framework for transmission expansion planning in deregulated environments, IEEE Trans. Power Syst. 24 (2) (2009) 1051–1061.
[30] B. Rashedi, A. Askarzadeh, A multi-objective approach for solving transmission expansion planning problem considering wind power uncertainty, Evol. Intell. 15 (1) (2022) 497–511, https://doi.org/10.1007/s12065-020-00525-2. Mar.
[31] A.N. de Paula, E.J. de Oliveira, L.W. de Oliveira, L.M. Honório, Robust static transmission expansion planning considering contingency and wind power generation, J. Control Automat. Electric. Syst. 31 (2) (2020) 461–470, https://doi.org/10.1007/s40313-019-00556-w.
[32] C. Rathore, R. Roy, Impact of wind uncertainty, plug-in-electric vehicles and demand response program on transmission network expansion planning, Int. J. Electric. Power Energy Syst. 75 (2016) 59–73, https://doi.org/10.1016/j.ijepes.2015.07.040. Feb.
[33] A. Monticelli, A. Santos, M.V.F. Pereira, S.H. Cunha, B.J. Parker, J.C.G. Praça, Interactive Transmission Network Planning Using a Least-Effort Criterion, 101, IEEE Transactions on Power Apparatus and Systems, 1982, pp. 3919–3925, https://doi.org/10.1109/TPAS.1982.317043. PAS-.
[34] Y. Lei, An incremental reliability assessment approach for transmission expansion planning, IEEE Transactions on Power Systems 33 (3) (2017) 2597–2609, https://doi.org/10.1109/TPWRS.2017.2756261.