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Transmission expansion planning optimization by adaptive multi-operator evolutionary algorithms

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ABSTRACT

This paper proposes a new evolutionary algorithm to solve transmission expansion planning problems in electric power systems. In order to increase the robustness of the search process and to facilitate its use by planners on different networks and operation conditions, the proposed method uses multi-operators and a mechanism for dynamic adaptation of the selection probabilities of these operators. Two sets of search operators are proposed: evolutionary and specialized. The mathematical formulation considers a DC network model including transmission losses and the "N-1" deterministic criterion. The proposed method is applied to a well known academic test system and a configuration of the Brazilian network.

1. Introduction

From a future scenario of power demand and generation, the main objective of the transmission expansion planning (TEP) problem is to find the best set of reinforcements for the transmission network that ensures an adequate power supply to consumers. Thus, the solution of a static TEP problem must specify where and how much transmission equipment must be installed in the power grid, to meet the energy market needs. However, in addition to having the lowest possible investment cost, TEP problem solutions must meet certain quality specifications in terms of services [1,2].

Traditionally, in order to ensure the security criteria, TEP problems have been solved by deterministic models such as the well known "N-1" and "N-2" [1,2]. In many cases, however, the obtained plan can lead to high investment costs. Moreover, although probabilistic models are capable of measuring the quality of a power network performance [1–4], there is no clear definition of how reliable a system must be based on reliability indices such as LOLE (loss of load expectation) or EENS (expected energy not supplied) [1,3], mainly because these indices are dependent on the load model and operating practices. Once the electric companies have not reached a consensus on these issues, they have preferred to keep the deterministic models and criteria in relation to probabilistic ones.

Currently, the solution of TEP problems for real systems is a highly complex stochastic combinatorial optimization task. Due to the large size of existing transmission systems, competitive energy market, and involved uncertainties (e.g., growth of load and generation, new types and location of generating sources, random behavior of transmission equipment and generation, etc.), the optimal TEP solution becomes almost unreachable. Even when the uncertainties are ignored, the complexity in terms of data, models, and computational effort is still very high, especially if the reinforcement timing is deemed (e.g., chronological stages). In this context, the TEP problem can be solved by mathematical models using classical optimization techniques [5,6] or by metaheuristics optimization techniques [7–17]; the latter being the focus of this work.

Optimization techniques based on metaheuristics have proven to be excellent tools in solving TEP problems for medium and large networks, finding high quality solutions with a relatively low computational cost [7–17]. The great advantage of these techniques is their ability to conduct global search, avoiding local optima and exploring efficiently the search space. Several algorithms have been proposed for the TEP problem: tabu search (TS) [7], greedy randomized adaptive search procedure (GRASP) [8], genetic algorithms (GA) [9,16], evolution strategies (ES) [10] differential

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evolution (DE) [11], artificial immune systems (AIS) [12] ant colony optimization (ACO) [13,14], and particle swarm optimization (PSO) [15,17]. Metaheuristic optimization techniques based on GA, ES, DE, and AIS are part of the family of evolutionary algorithms (EA), since they use probabilistic-based methods to simulate the process of evolution by means of natural selection [18].

Despite the success that EAs have shown in solving difficult optimization problems, the computational performance of these methods heavily depends on the correct setting of the control parameters and operating mechanisms, such as population size, type of search operators and their application rates, selection and replacement strategies, etc. [19]. The decision on which search operators must be used and how often is a challenge in the development of EAs, and has encouraged the development of various techniques and adaptive strategies for the control parameters [19–24]. Since each operator encapsulates a particular search strategy, keeping a set of operators in the same algorithm contributes to the robustness of the search process. To effectively select the operators, probabilistic adaptive strategies have been used. Thus, the best one will be automatically chosen depending on the type of problem being solved and on what stage the evolutionary process is [22].

The paper proposes a new metaheuristic optimization method solve TEP problems based on EA concepts. The search algorithm uses multi-operators and a mechanism for dynamic adaptation of the selection probabilities, associated to these operators, to increase the robustness of the search process. Two sets of stochastic search operators are proposed: evolutionary operators and specialized operators. The formulation of TEP solutions are based on a DC network model with losses and the “N-1” security criterion. The performance of the TEP method is evaluated through its application in two systems well known in the area: IEEE RTS-79 and a configuration of the Southern Brazilian network.

2. Adaptive operator selection

First, the proposed method carries out an online evaluation of the performance of the operators at each stage of the search process of TEP solutions. Basically, it includes an automatic and dynamic adjustment of probabilities for selecting the most appropriate operators. The proposed EA, in principle, may use any number of search operators, whether “pure” evolutionary or TEP specialist. In this section, the basic theoretical concepts of adaptive strategy adopted in this work will be presented, along with the traditional evolutionary operators.

2.1. Basic concepts

Several adaptive strategies have been proposed in the area of evolutionary computation literature, for instance: probability matching and adaptive pursuit (AP) [20], outlier detection [21] multi-armed bandits [22]. In this work, the idea is to define a strategy that is simple to use with few control parameters to adjust, and also with a good computational efficiency when applied to TEP problems. Thus, the AP strategy is adopted, which makes direct use of information of the evolutionary process to automatically adjust the EA control parameters.

2.1.1. Operator evaluation

The idea is to measure the quality of the operator performance, assigning credits according to the productivity of the operator and quantifying its efficacy in the search process. The approach most commonly used to assess the productivity of operators is the improvement in fitness function, brought by generated offspring [24]. Thus, each operator i, after being applied to one or more individuals in the population, will generate a single newborn offspring and will have its credit r_i calculated on the basis of the existing fitness gain, between parent (reference) and offspring, so that:

$$r_i = \mathrm{Max}\left[0,\ \left(\frac{f_P - f_F}{f_P}\right)\right] \tag{1}$$

where f_P and f_F are, respectively, the values of fitness function for the parent and offspring; Max[.] function takes two values and returns the largest one. The operator receives zero credit when it does not produce a better offspring compared to the its parent, i.e., if $f_P < f_F$ then $r_i = 0$.

Given an EA with a set of K operators, at each T generations of the evolutionary cycle, a specific operator i is run M_i times, and each run produces a credit $r_i(j)$, with $i = 1,\ldots,K$ and $j = 1,\ldots, M_i$. Thus, the normalized average reward for the i operator, i.e., R_i, is evaluated by:

$$R_i(t) = \left[\frac{1}{M_i}\sum_{j=1}^{M_i} r_i(j)\right]\frac{1}{R_{\mathrm{Max}}} \tag{2}$$

where each “time” t is relative to an adaptive cycle incremented by a period of T generations (time steps) of EA; and R_{Max} is the highest average of received credits, considering the K operators. As the magnitude of the credits change significantly during the evolutionary process, the average obtained rewards are individually normalize by the operators, so that, regardless the current stage of the search process, $0 \le R_i(t) \le 1$.

The value Q_i specifies an estimate for the quality of operator i, due to its received reward, R_i, during the evolution process, also considering the history of rewards: Q_i quantifies how good the i operator has been for the current search stage. For each adaptive cycle, Q_i is updated as follows:

$$Q_i(t+T) = Q_i(t) + \alpha\,[R_i(t+T) - Q_i(t)] \tag{3}$$

where α is the quality update rate, such that, $0 \le \alpha \le 1$. Parameter α controls the memory of the adaptive selection operators, where $\alpha = 1$ results in a system without memory and with a maximum update, and $\alpha = 0$ results in a system with maximum memory, but without any updates. The basis for memory insertion in the adaptive EA is to minimize the effect of sudden changes arising from good local operator performance.

2.1.2. Adaptation probability

This is the mechanism used to perform the adaptation of the selection probabilities of operators, transforming the values Q_i in a probability distribution. In this context, the use of AP strategy aims to update of the probability distribution, to maximize the use of the best quality operator. Thus, for a given time t, the operator i of the set of K operators have probability $P_i(t)$ of being selected and applied to one or more individuals of the current population. In order to ensure that operators are active during the entire search process, values of minimum and maximum probabilities ($P_{\min}$ and $P_{\max}$) are included into the AP strategy, such that: $P_{\min} \le P_i(t) \le P_{\max}$; $P_{\max} = 1 - (K-1)P_{\min}$; and $\sum P_i(t) = 1$.

Once the best i^* operator is identified for the current search stage, i.e., the operator with the highest value Q_i, the adaptation of the probability distribution is carried out as follows:

$$\begin{cases} i^* = arg\max\left\{Q_i(t+T)\right\}, & \text{for} \quad i = 1, \ldots, K \\ P_i(t+T) = P_i(t) + \beta\,[P_{\max} - P_i(t)], & \text{if} \quad i = i^* \\ P_i(t+T) = P_i(t) + \beta\,[P_{\min} - P_i(t)], & \text{if} \quad i \ne i^* \end{cases} \tag{4}$$

where argmax{.} function returns the index of the highest quality operator; and β is the adaptation rate of probabilities, such that: $0 \le \beta \le 1$. It is observed that for the relationship $P_{\max} > P_{\min}$ to be true, which is desirable for the adaptation process, the $P_{\min} < K^{-1}$