Evolutionary Optimization of Flexible AC Transmission System Device Placement for Increasing Power Grid Reliability

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Abstract

In order to increase the reliability of the nation's power grid, this paper proposes using an Evolutionary Algorithm (EA) to optimize the placement of a limited number of Flexible AC Transmission System (FACTS) devices on power lines. We benchmark against a brute-force placement and compare our EA approach with a greedy algorithm approach suggested by previous research to show that the EA approach results in superior placements.

Keywords: Critical Infrastructure Protection, FACTS, Placement, Evolutionary Algorithm.

1 Introduction

Our nation is becoming ever more dependent on its electrical power grid, while at the same time the power grid is becoming increasingly vulnerable to both natural and intentional disruption [6]. Increasing the reliability of our power grid is therefore of paramount importance.

Some of the major causes for the power grid's increased vulnerability are:

- less spare line capacity - causing the system to run close to its operating limits which results in what is known as a *stressed system*
- a higher degree of interconnectedness between regional subgrids - this greatly increases the risk of a *cascading failure*[1] to spread to other subgrids
- a more hostile post-9/11 environment - while before 9/11 the greatest worry in regard to disruptions were natural disasters (e.g., a falling tree bringing down a power line), since then there has been concern that hostile interests (e.g., terrorists) might conceivably seek to attack the power grid physically and/or via cyberspace

In order to increase the reliability of the nation's power grid, we propose addressing the above listed vulnerabilities by placing a limited number of Flexible AC Transmission System (FACTS) devices [5] on specific power lines. A FACTS device is capable of limiting the amount of power as well as the direction in which power flows. Working together, FACTS devices can prevent cascading failures. These devices are, however, very expensive (in the order of millions of dollars); it is, therefore, only economically feasible to place a limited number, making a (near) optimal placement critical.

The placement of these devices is a computationally intensive problem on the order of $\binom{n}{k}$ with n being the number of power lines and k being the number of FACTS devices. In addition, the non-linear dependencies between device placements, due to a system of non-linear partial differential equations, is expected to cause complex local optima in the search space.

2 Background

For comparative purposes we have implemented an iterative greedy FACTS device placement algorithm (see Algorithm 1) based on the greedy algorithm presented in [1]. It iteratively places a FACTS device on the most frequently overloaded line and then recalculates how often each line is overloaded.

The power industry recognizes three warning levels for line overloads, each of which is associated with a power threshold. An overload warning is triggered when the power flow across a line is greater than *threshold* times the rated line capacity. Level 1

[1] Where the outage of one line places load on additional lines, causing them to fail as well. In the extreme case, this can cause a power outage in a large area such as the August 14, 2003 incident [6] that resulted in a loss of power to significant portions of Michigan, Indiana, Conneticut, Ontario, and almost all of New York.

Algorithm 1 Iterative Greedy FACTS Placement

$P \leftarrow \emptyset$
$l \leftarrow$ number of lines
$f \leftarrow$ number of FACTS devices
for $FACTS = 1$ to f **do**
  $LO[i] = 0,\ i \in 1 \ldots l$
  for $SLC = 1$ to l **do**
    $LF \leftarrow Power\_Flow\_Model(P)$
    for $k = 1$ to l **do**
      if $LF[k] > threshold \cdot LC[k]$ **then**
        $LO[k] \leftarrow LO[k] + 1$
      end if
    end for
  end for
  $P \leftarrow P \cup ArgMax(LO[i]),\ i \in 1 \ldots l$
end for

($threshold = 1.0$) is the lowest warning level, where the system can remain operational but needs to be closely watched, Level 2 ($threshold = 1.1$) is the next warning level, where the system can still operate for a reasonable period of time but action needs to be taken. Level 3 ($threshold = 1.2$) is an emergency level, where lines will begin to burn out if nothing is done quickly.

The greedy algorithm works as follows for a given power system, where LC is an array containing that system's line capacities. The set P of line numbers indicating placed FACTS devices is initalized to empty, while l and f are initialized to the number of power lines and the number of FACTS devices to be placed, respectively. The algorithm works by iterating over the number of FACTS devices to be placed. LO is an array that keeps the tally of how many times each line has been overloaded in the current iteration. It gets reset to zero for each iteration. This tally is increased each time a line is overloaded, for every Single Line Contingency (SLC)[2]. Overloads are determined by running $Power\_Flow\_Model(P)$ —which is an implementation of the powerflow algorithm described in [4]— on the system for the current P, assigning the computed power flow values for each line to the array LF, and for each line comparing these values with *threshold* times that line's capacity. The most frequently overloaded line is determined at the end of each iteration. Placement of a FACTS device on that line is indicated by adding the line number to P. After the final iteration, P contains the greedy algorithm's FACTS placement solution in the form of a set of line numbers.

[2]An SLC is the outaging of a single line.

Table 1: EA Specifics

Representation	Var. Length Integer Sequence
Initialization	Uniform Randomly
Parent Selection	Linear Rank Based
Recombination	Custom (see Subsection 3.1)
Mutation	Custom (see Subsection 3.2)
Competition	Elitist Stochastic ($\mu + \lambda$)
Termination	Fixed # of Generations

3 Evolutionary Algorithm

The specifics of our EA are summarized in Table 1. In its most general form, an individual encodes the placement of an arbitrary number of FACTS devices; this is represented by a variable length integer sequence with each integer specifying a line number. A restricted form, in which an individual encodes the placement of a prespecified number of FACTS devices, was also implemented; this is particularly useful for plotting the aggregate number of overloaded lines versus the number of FACTS devices (see Section 4). The remaining EA details are explained in the following subsections.

3.1 Reproduction

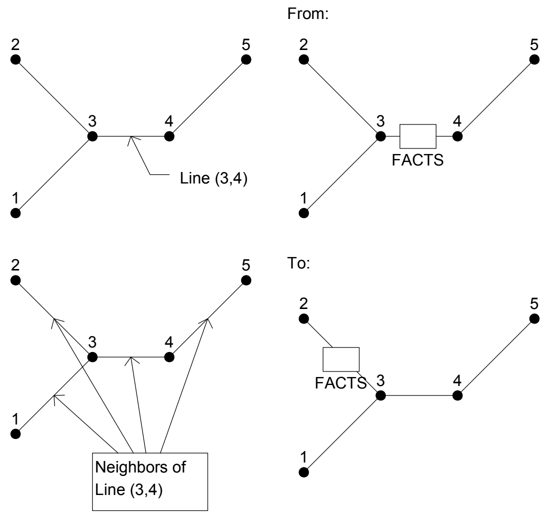
Individuals are selected stochastically from the population pool according to the linear rank formula presented in Section 25.2 of [2]:

$$Pr_{rank}(i) = \frac{\alpha_{rank} + \left[\frac{rank(i)}{(\mu-1)}\right](\beta_{rank} - \alpha_{rank})}{\mu} \quad (1)$$

where μ is the population size, $rank(i)$ is the rank of individual i where 0 is least fit and $\mu - 1$ is most fit, α_{rank} is the expected number of offspring for the least fit member and can be shown to be equal to $2-\beta_{rank}$, and β_{rank} is the expected number of offspring for the fittest member. β_{rank} is a user adjustable parameter that can be varied between 1.0 and 2.0, higher values producing a steeper curve; we chose 2.0 in order to obtain high selective pressure.

When an individual is selected to reproduce, it will recombine with chance P_c with another member, rather than simply being cloned. In recombination, each individual FACTS device placement from both parents has a 50% chance of being passed on to the offspring. If the number of FACTS placements has been prespecified, the list is either truncated or padded with random placements as required.

Figure 1: Examples of neighboring lines (left) and neighboring FACTS placements (right).



3.2 Mutation

Each offspring is selected with chance P_m for mutation, in which each individual FACTS placement has a $1/n$ chance of being moved, where n is the number of FACTS placements in that member. Thus, while on average one FACTS placement is moved per mutation, there is a chance for multiple placements to be moved. This prevents the EA from getting stuck in local optima from which the movement of a single placement would not be sufficient to escape.

FACTS placement movement is performed according to the system's topology. A line is a neighbor of another line when it shares a bus with that line. A FACTS placement, when chosen for mutation, is randomly moved from the line it is on to one of its neighbors[3], as shown in Figure 1.

3.3 Evaluation

To evaluate an individual, $Power\_Flow\_Model(P)$ is run on the system for the set of FACTS placements it encodes. An individual's fitness is inversely proportional to the aggregate number of overloads over all SLCs (different types of overloads can be specified by choosing the appropriate *threshold* value). Running $Power\_Flow\_Model(P)$ is numerically intensive: it takes on the order of a minute to execute on a Pentium P4 for a small system like the IEEE 118 bus test system [3] which contains only 179 lines.

[3]note that in our definition of neighboring line, a line is its own neighbor

Table 2: Parameter Sets

Param. Set	P_c	P_m	μ	λ	*Gens*
EA1	0.20	0.50	100	2	100
EA2	0.90	0.90	100	4	100

Table 3: Aggregate Level 1 Overloads

# FACTS	Greedy	EA1 Best	EA1 Avg	EA2 Best	EA2 Avg
1	41	37	38.2 (1.10)	37	37 (0.00)
2	40	35	36 (1.22)	35	35 (0.00)
3	40	34	35.4 (1.14)	34	34.6 (.89)
4	40	34	35.8 (1.30)	31	32.4 (1.14)
5	40	34	34.6 (.55)	31	31.6 (.55)
6	40	32	33.2 (1.30)	31	31.8 (.45)
7	40	30	31.8 (1.10)	30	30.4 (.89)
8	39	31	31.8 (.45)	29	29.8 (.84)
9	39	29	30.4 (.89)	28	29.4 (.89)
10	38	31	31.2 (.45)	26	27.6 (1.14)

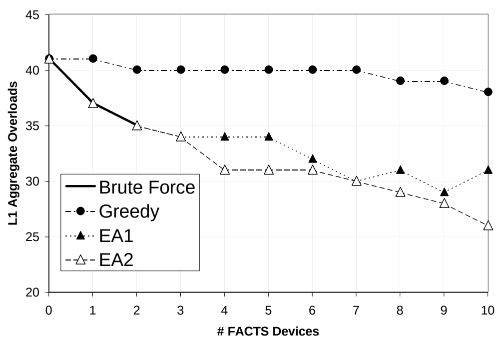
3.4 Competition

Of the combined population and offspring pool, λ individuals are selected for elimination employing the inverted version (fittest individual ranked lowest instead of highest) of the linear rank based model used for reproduction, again with β_{rank} held at 2.0. This model constitutes an Elitist approach, since the fittest member has a zero probability of being chosen.

4 Experimental Results

We compared the performance of our EA to that of the Iterative Greedy FACTS Placement algorithm on the aforementioned IEEE 118 bus system. For performance measure we chose minimizing the aggregate number of Level 1 overloads (see Section 2); therefore *threshold* was set to 1.0 for both the greedy algorithm and our EA's fitness function. We report results for the two EA parameter sets specified in Table 2. Parameter set EA1 was our initial parameter set; it was designed to produce high selective pressure in order to minimize the number of evaluations required in light of the high computational cost of evaluation. After studying the effects of varying various of the parameters, we eventually arrived at parameter set EA2. The results for parameter sets EA1 and EA2 as well as for the greedy algorithm are provided in Table 3. Results are reported for one

Figure 2: Comparison of selected algorithms on the IEEE 118 bus test system.



through ten FACTS devices (with the number prespecified for the EA). Due to the high computational cost of the fitness function, only five runs were performed on each parameter set. The columns EA1 Best and EA2 Best contain the best results found over all five runs, while columns EA1 Avg and EA2 Avg list the average best results; standard deviations are indicated in parentheses.

The results are plotted in Figure 2. The graph shows the baseline number of overloads before any FACTS devices are placed, which is 41. The graph also displays the result of an exhaustive search for one FACTS placement, which is 37 overloads, and for two FACTS placements, which is 35 overloads. While it is not feasible to perform an exhaustive search for higher numbers of FACTS devices, it is encouraging that for both parameter sets the EA found the optimal placement for one or two FACTS devices. Parameter set EA2 is clearly superior to EA1, while in both cases the EA obviously outperforms the greedy algorithm.

5 Conclusions

The increasing dependence of our nation on its power grid makes the robustness and integrity of the power grid ever more critical. The placement of power regulation devices, such as FACTS devices, is an important tool for protecting power grids from catastrophic failures. Placement is critical for obtaining optimal benefits from these devices. Prohibitively high costs for FACTS devices make it essential to obtain the maximum benefit from the minimum number of devices. The EA presented in this paper was demonstrated to be superior to the Iterative Greedy FACTS Placement algorithm suggested in previously published work. The customized recombination and mutation operators proved effective for this particular placement problem and are expected to be similarly effective on other placement problems.

6 Future Work

There are many possible avenues of research leading from the above discussion. Some we plan to investigate in the near future are:

- Study the scalability of our EA by applying it to larger IEEE test systems.
- Parallelize our approach in order to utilize a grid computing cluster.
- Switch to a more realistic fitness function which balances minimizing the aggregate number of overloaded lines and minimizing the aggregate amount of overloaded power (the greater a line's capacity, the more important that it not be overloaded).

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