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Mitigating energy loss on distribution lines through the allocation of reactors

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Abstract. This paper presents a methodology for automatic reactors allocation on medium voltage distribution lines to reduce energy loss. In Brazil, some feeders are distinguished by their long lengths and very low load, which results in a high influence of the capacitance of the line on the circuit’s performance, requiring compensation through the installation of reactors. The automatic allocation is accomplished using an optimization meta-heuristic called Global Neighbourhood Algorithm. Given a set of reactor models and a circuit, it outputs an optimal solution in terms of reduction of energy loss. The algorithm is also able to verify if the voltage limits determined by the user are not being violated, besides checking for energy quality. The methodology was implemented in a software tool, which can also show the allocation graphically. A simulation with four real feeders is presented in the paper. The obtained results were able to reduce the energy loss significantly, from 50.56%, in the worst case, to 93.10%, in the best case.

1. Introduction

The study presented on this paper is part of a Research & Development (R&D) Project from ANEEL (Brazilian Electric Energy Regulator Agency) developed jointly by the Energisa Group and Daimon Engineering & Systems. The Energisa Group is one of the main private owned companies of Brazilian electricity industry and operates in distribution, generation and transmission of electric energy, controlling 13 distribution utilities. The group is present in 788 cities and meets around six million consumers, corresponding to about 16 million people.

Energisa’s medium voltage distribution system presents, in some parts of Brazil, feeders distinguished by their long lengths (> 100 km) and very low load. These regions are commonly country farming areas, resulting in a high relation of installed power per consumer.

The characteristics mentioned previously result in two main consequences: high influence of the capacitance of the line on the circuit’s performance and the occurrence of the Ferranti effect [1], which makes the voltage at the receiving end of the distribution line to be greater than the voltage at the sending end. In this situation, the power delivered to the consumers presents capacitive nature with low power factor, provoking intense increasing in the energy loss. That being said, the main goal of this Project is to decrease this loss.

The most common procedure applied by the electric industry in order to minimize reactive power in medium voltage feeders and, consequently, reduce energy loss consists in the installation of capacitors
in the lines [2]-[8]. Obviously, this approach is not an option to the presented situation, once it is suitable to the opposite condition, in which the reactive is of inductive nature.

In the literature, there are some works reporting the allocation of reactors for reactive compensation [9]-[12]. However, they describe the installation of reactors on substation bars, in which the goal is not the reduction of energy loss [9]-[11], or they do not perform an automatic allocation [12]. Thus, given a feeder and a set of reactor models, this paper describes a software tool able to propose an optimal solution concerning the reduction of energy loss through an automatic reactor allocation. Beyond that, the tool is also able to verify if the desired voltage limits are not violated as well as to make a resonance analysis, checking for energy quality.

The solution is built by the Global Neighbourhood Algorithm (GNA), an optimization technique for combinatorial problems [13]. This method was presented in 2013 for the first time and explores global and local optima together to find an optimal solution.

The next section explains the theory behind GNA. Section 3 describes the new methodology used to solve the mentioned problem. Then, Section 4 presents the results obtained by it and, finally, conclusions and comments are made in the last section.

2. Global neighbourhood algorithm

Combinatorial optimization problems, as the one presented in this paper, have a finite number of possible solutions. Thus, the best way to solve them would be to evaluate each possible solution and to determine the best one, in an exhaustive manner. However, in most cases, this approach is not practical, once the number of possible solutions is very high, which leads to a very expensive process in terms of computational time.

In order to overpass this obstacle, the meta-heuristic methods were developed. These methods are able to find an optimal solution in much less time by exploring a subset of the search space in a smart way.

The Global Neighbourhood Algorithm (GNA) is a meta-heuristic suitable for solving combinatorial problems. This kind of problem can present a series of local optima, so the GNA works through two basic actions: exploration and exploitation. The exploration investigates all the search space while the exploitation searches for other solutions around a specific solution, which will be the best one found so far by the algorithm. It is also a population based iterative method, which means that a new population (set of solutions) is created at each iteration [13].

Before the algorithm’s execution, an objective function is defined, which will be maximized (or minimized). Thus, the best solution is the one that provides the best result of the objective function compared with the other solutions [13].

Then, it is possible to start the optimization process. The first population is randomly generated, which means the solutions can be in any part of the search space. After, they are evaluated and the best solution, according to the objective function, is saved [13].

In each of the next iterations, a new population is created, in which half of the solutions is randomly constructed and the other half is generated by the investigation of the search space around the best solution found so far. Thus, local and global searches are made simultaneously. The process continues following this logic, the new solutions are evaluated, and the best solution is updated. The algorithm is finished when a predetermined number of iterations is reached. Then, the best solution found during the whole process is chosen [13].

3. Methodology

This section describes how the GNA was implemented in this application in order to determine an optimal solution of automatic reactors allocation in a medium voltage distribution line aiming the mitigation of energy loss. The following subsections define some concepts and processes used in the methodology. They are: (3.1) modelling; (3.2) objective function; (3.3) constraints; (3.4) local search; (3.5) tabu list; (3.6) inputs; (3.7) reactor installation probability; (3.8) output; and (3.9) the algorithm.

3.1. Modelling
Firstly, it is necessary to define two sets: the set of bars B and the set of reactor models R. In a simple example, there is a feeder with 100 bars and four models of reactor available. Thus, the sets are: 

\[ B = \{1, 2, 3, \ldots, 100\} \text{ and } R = \{a, b, c, d\} \]

In this way, a solution indicates the bars in which a reactor was allocated and the respective model. From the last example, a solution could be \( X = \{(10, a), (30, c), (81, b)\} \). It means that one reactor of type “a” was installed at bar 10, one of type “c” at bar 30, and one of type “b” at bar 81. In the other bars no reactor was installed.

### 3.2. Objective function

The objective function is responsible for evaluating the solutions, so they can be compared to each other, making possible to tell which one is the best. In the results presented in this paper, the energy loss represents the objective function. The energy loss is measured in MWh/month. Thus, the lower its value, the better is the solution.

### 3.3. Constraints

Some solutions generated throughout the algorithm are not feasible in a real application in the electric system. Thus, some constraints must be considered in order to guarantee the feasibility of the solutions. In this tool, two constraints were applied. The first one refers to the voltage limits. A solution is considered unfeasible if the voltage value at any bar is out of the range allowed by the user. The second constraint consists in checking for energy quality. The allocation of a reactor in a capacitive circuit produces the amplification of electric current for a determined frequency value, a phenomenon called resonance, which can lead to several damages to the line and its pieces of equipment. In case the resonance frequency, which is a function of the reactor power and the capacitance of the line, is near any harmonic of the operation frequency of the system (60 Hz, in Brazil), the solution that suggested the allocation is marked as unfeasible. Thus, any solution that violates at least one of the mentioned constraints must be dismissed.

### 3.4. Local search

As described in section II, from the second iteration of the algorithm, each new population is divided in two: half of it is randomly built and the other half is based on the best solution found so far. In the second case, a (local) search is done around the best solution, that is, solutions located in its neighbourhood must be created and evaluated, attempting to find a local optimum. Thus, given a solution, it is necessary to define what a neighbour solution means. Theoretically, a local search has the goal to find solutions similar to another one. In the case of reactor allocation, a similar (neighbour) solution must: (1) have reactors at the same bars of the original solution, but with different models; and / or (2) have reactors of any model in one, and just one, bar near to the each bar in which a reactor was installed in the original solution. The interval that defines if a bar is near another one is chosen by the user previously the allocation. Its value defines the bars that can be considered when building a neighbour solution.

### 3.5. Tabu list

An enhancement was implemented in the GNA technique in order to improve the quality of the answers. It consists in a list of solutions that cannot be chosen again, called tabu list. During the local search process, some solutions near the best solution are created and evaluated. However, once the local search space is not as big as the total space and that some solutions can remain as the best one for many iterations, repeated solutions can be created, which affects the efficiency of the algorithm. The tabu list was developed to solve this problem. As soon as a neighbour solution is created it is added to the tabu list. Then, when the next neighbour solution is created, if it is already in the tabu list, another solution must be created in its place. If not, it remains in the current population and it is also added to the tabu list. The list is only reset when the best solution is altered. The number of possible neighbour solutions is restricted to the interval bar range used in the local search. So, when the tabu list is too big, it can be difficult to generate a solution that is not in the list.
and the algorithm could be stuck. In order to avoid that, two moves are possible: (1) in case after three attempts it is not able to create a solution different from the ones in the tabu list, the algorithm goes to the next step; and (2) in case the number of possible neighbour solutions that are not already in the tabu list is lower than half the population, all the next populations must be randomly generated until a new best solution is found and consequently the tabu list is reset.

3.6. Inputs
The software user needs to provide some input data in order to start the allocation algorithm. Firstly, it must determine the feeder to be studied and the reactor models available. The models must inform the reactive power, in kVAr, at each period of the day (night, morning, afternoon, and evening – each one has six hours of duration).

The user must also choose the number of populations (iterations) he or she wants to analyse and the number of solutions per population. It is important to highlight that as the numbers of populations and solutions per population increase, the probability to find a better solution increases. However, the computational processing time will also increase.

As mentioned before, the range of near bars for the local search process and the voltage limits tolerated are also chosen by the user.

Finally, it is also possible to inform the maximum number of reactors allowed. In case no value is chosen, the algorithm is free to allocate any number.

3.7. Reactor installation probability
The probability of installing a reactor in a bar is calculated as a function of the number of bars in the feeder, the reactor models available and the capacitive power present in the line. This probability is useful in the construction of random solutions. According to it, a reactor is installed in each bar of the circuit. Eq. (1) defines it mathematically:

\[
\text{Prob}_{\text{reac,bar}} = \frac{P_{\text{pot, \text{cap}}}}{N_{\text{bars}}} 
\]

Where:

- \(\text{Prob}_{\text{reac,bar}}\) is the reactor installation probability per bar.
- \(P_{\text{pot, \text{cap}}}\) is the largest reactive power considering the four periods of the day, in kVAr.
- \(P_{\text{ave, reac}}\) is the average power of the reactor models available, in kVAr.
- \(N_{\text{bars}}\) is the number of bars in the circuit.

3.8. Output
The best solution found during the process is presented at the end of the algorithm. It shows the bars in which a reactor will be allocated, and the respective models followed by the result of the objective function: the energy loss, in MWh/month.

The allocation is also presented graphically.

3.9. The algorithm
Once some concepts were defined in the previous subsections, it is possible to describe step by step the GNA applied to reactor allocation.

Firstly, the user inserts the inputs: feeder to be studied; reactor models available; number of populations (iterations) and solutions per population; number of near bars for the local search; voltage limits; and the maximum number of reactors to be allocated (optional).
The reactor installation probability is calculated before the first iteration, as described in subsection 3.7. With this value at hand, it is possible to create random solutions and start the algorithm. The first population is created randomly. For each solution, all the bars are visited and, according to the calculated probability, a reactor is installed. The solutions considered to be unfeasible following the constraints specified in subsection 3.3 are dismissed. The other ones are evaluated by the objective function and the best one is saved.

The second iteration starts, and half of the population is created randomly as done in the first iteration. The other half is built based on the best solution found in the last iteration, as explained in subsection 3.4. At this point, the tabu list (subsection 3.5) acts, avoiding repeated solutions. After the second populations is created, the best solution is selected and in case it is even better than the last one, the best solution is updated.

Then, from the third iteration, two conditions can occur: (1) each half of the population is built in a different way; or (2) the whole population is created randomly. The first case happens when the best solution is altered or when the number of possible solutions to be built around the current best solution is greater or equal to half the population. If not, the second condition is activated. The best solution continues to be updated when needed.

The process goes on until the pre-determined number of iterations is reached. At the end, the best solution found is chosen and presented to user, as mentioned in subsection 3.9.

4. Results
Some simulations were made in four real feeders from the Energisa Group in order to show the results that can be obtained by the tool. The feeders are located in Mato Grosso do Sul state, Midwest of Brazil. Due to some geographic and economic peculiarities of this region of Brazil, their feeders present the attributes that motivated this Project: long lengths and low load.

The values achieve by the new tool are compared with the values of energy loss in the feeders without reactor allocation as well as with the current configuration of the circuits, in which there are some reactors allocated by the company through other methods.

The input variables in the simulations were: 20 iterations; 20 solutions per population; 10 near bars in local search; voltage allowed between 0.95 p.u. and 1.05 p.u.; and the maximum number of reactors was not determined, so the algorithm was free to allocate any number.

The reactor models with their values of reactive power at each period of the day are available on Table 1. Two of them are fixed (the same reactive power all day) and the other two change their power along the day.

| Model | Power in kVAR (night) | Power in kVAR (morning) | Power in kVAR (afternoon) | Power in kVAR (evening) |
|-------|-----------------------|-------------------------|---------------------------|-------------------------|
| 1     | 500                   | 500                     | 500                       | 500                     |
| 2     | 1000                  | 1000                    | 1000                      | 1000                    |
| 3     | 500                   | 1000                    | 500                       | 1000                    |
| 4     | 1000                  | 500                     | 1000                      | 500                     |

Table 2 shows the amount of energy loss for each feeder and for each of the three scenarios: (1) with no allocation; (2) at the current configuration (with the numbers of reactors in parentheses – all model 1); and (3) with the allocation made by the new tool. In addition, it is presented the processing time spent. The computer used in simulations has an Intel® processor Core™ i5-2410M @ 3.30 GHz and 3.00 GB RAM memory.

| Feeder | Energy with no allocation (MWh/month) | Energy loss after allocation (MWh/month) – current | Energy loss after allocation (MWh/month) – new methodology | Processing time (s) |
|--------|--------------------------------------|----------------------------------------------------|-----------------------------------------------------------|---------------------|

Table 1. Reactors models.

Table 2. Feeders and their energy loss.
configuration¹

| Feeder | Reduction 1¹ | Reduction 2² |
|--------|--------------|--------------|
| ACA51  | 86.43%       | 73.01%       |
| BON51  | 93.10%       | 87.58%       |
| CSU52  | 55.62%       | 30.08%       |
| NAN51  | 50.56%       | 26.93%       |

¹The values in parenthesis indicate the number of reactors at the current configuration, allocated by the company. All of them are of model 1.

Table 3 shows the loss reduction rate achieved by the new tool in relation to the feeders without reactors (reduction 1) and to the current configuration (reduction 2).

Table 3. Energy loss reduction rate.

Tables 2 and 3 show the allocation is able to significantly reduce the energy loss in the studied feeders. Considering the reductions in relation to the feeders with no reactors, the results varied from 50.56%, in the worst case, to 93.10%, in the best case. In relation to the current configurations, the results varied from 26.93%, in the worst case, to 87.58%, in the best case.

In Figs. 1 to 4, the feeders are graphically presented with the places where the reactors were installed, and their models are indicated with numbers. The figures are shown just to illustrate the allocation and to provide a spatial sense of it. The specific places of the allocation bars are specified by the algorithm, but were not presented for simplification.

The results indicate the efficiency of the developed tool, which is able to consider all reactor models available and find an optimal solution for each feeder, taking into account voltage limits and resonance problems. More than that, it is possible to set the maximum number of reactors in order to meet eventual budget restrictions of the company.

![Figure 1. Feeder ACA51 and the allocation proposed by the new methodology. One model 1 and one model 2 reactors were installed.](image)
Another important advantage is the speed and usability of the new tool. In a few minutes, it was able to present results better than the current ones, which were given by other methodologies, which spent more time and resources.

5. Conclusions
This paper described a new methodology for reactors allocation in medium voltage circuits. This methodology is motivated by the existence of feeders with long lengths and low load, resulting in a high influence of the capacitance of the line over the circuit’s performance and, consequently, in high levels of energy loss. The reactors allocation is capable of balancing this effect, decreasing the losses. In this way, a tool able to make the allocation automatically has been proposed. An optimization technique called Global Neighbourhood Algorithm (GNA) was applied, which is able to combine global and local searches aiming to an optimal solution.
The user can choose some input parameters. They are: reactors models; voltage limits; numbers of reactors (optional – if not chosen, the algorithm will freely determine); and other GNA specifications. Four feeders from the Energisa Group, which present the attributes mentioned earlier, were simulated to show the possible results provided by the new tool. These results were compared with energy loss values on the feeders with no reactors, and with values of the circuits’ current configurations, which have reactors allocated by other methods.

Through an analysis of energy loss reduction, comparing with a scenario with no reactors, a reduction of 50.56%, in worst case, and of 93.10%, in the best case, were achieved. Comparing with the current scenario, the reductions were also relevant: from 26.53% to 87.58%.

An important innovation of the new tool is its ability to achieve an optimal solution of automatic reactors allocation in practical time, considering many reactors models, besides checking for voltage limits and resonance effects on the circuit. These sets of variables and constraints make the analysis impractical for human evaluation alone, emphasizing the relevance of the developed software.

In the future, improvements will adjust the objective function in order to consider economics aspects like costs, as well as the energy loss reduction. Besides that, it is also possible to formulate an objective function able to consider predicted load growth rates, their impact at energy loss reduction and the benefits of the allocation throughout the reactors lifetime period.

6. References
[1] S Hong 1995 Forging Scientific Electrical Engineering. John Ambrose Fleming and the Ferranti Effect. Isis 86, pp. 30–51.
[2] N M Neagle, and D R Samson 1956 Loss Reduction from Capacitors Installed on Primary Feeders AIEE Transactions, EUA, Vol. 75, pp. 950-959.
[3] R F Cook 1959 Analysis of Capacitor Application as Affected by Load Cycle AIEE Transactions, Vol. 78, pp. 950-957.
[4] M E Baran, and F F Wu 1989 Optimal Capacitor Placement on Radial Distribution System ITPD, Vol. 4, pp. 725-734.
[5] H D Chiang, J C Wang, O Cockings, and H D Shin 1990 Optimal Capacitor Placements in Distribution Systems: Part I: A New Formulation and the Overall Problem ITPD, V. 5, N. 2, pp. 634-642.
[6] H Chin, and W Lin 1994 Capacitor Placement for Distribution Systems with Fuzzy Algorithm Proceedings of 1994 IEEE Region 10’s Ninth Annual International Conference, Vol. 2, pp. 1025-1029.
[7] J Teng, C Chen, C Chen and Y Liu 2008 Optimal capacitor control for unbalanced distribution systems with distributed generations IEEE International Conference on Sustainable Energy Technologies ICSET, pp.755-760, Singapore.
[8] M Kalantari, and A Kazemi 2011 Placement of distributed generation unit and capacitor allocation in distribution systems using genetic algorithm 10th International Conference on Environment and Electrical Engineering (EEEIC), pp.1-5, Rome, Italy.
[9] Z S Elrazaz 2001 Optimal Allocation of Reactors for Light Load Operation IEEE Proceedings – Gener Transm Distrib Vol. 148, Iss. 4, pp. 350-354.
[10] F S Chaves, and M H M Vale 2002. Controle de Tensão e Compensação Reativa – Procedimento Aplicado à Expansão de Sistemas Elétricos XIV Congresso Brasileiro de Autômático, Brazil.
[11] T M T S Alves 2011 Desempenho da Proteção de Reatores de Linhas de Transmissão frente a Manobras e Falhas Internas e Externas M.Sc. Thesis, University Federal of Rio de Janeiro, Rio de Janeiro.
[12] F E Corradi 2014 Redução de Perdas Técnicas em Redes de 34,5 kV com a Aplicação de Reatores para Compensação Reativa M.Sc. Thesis, University Federal of Mato Grosso do Sul, Campo Grande.
[13] A Alazzam, and H W Lewis 2013 A New Optimization Algorithm for Combinatorial Problems International Journal of Advanced Research in Artificial Intelligence (IJARAI), Vol. 2, No. 5.