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Optimal capacitor bank placement and sizing in the IEEE 34-node test model for loss reduction using Genetic Algorithm

Ubicación óptima y dimensionamiento de banco de capacitores en el modelo de prueba IEEE 34 nodos para la reducción de pérdidas mediante Algoritmo Genético

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Abstract

In order to amend disturbances such as: voltage drops, power losses, among others; because the loads in a real distribution system are unbalanced and these affect the quality and reliability of electric service. A mathematical optimization technique is presented through a genetic algorithm, where an objective function is proposed in order to minimize losses in the system. The objective of the genetic algorithm is to provide the optimal location and sizing of a capacitor bank in a distribution system. This method, being iterative, seeks the most feasible solution by means of its population, generation, reproduction probabilities and mutation variables in order to fulfill its objective function.

Keywords: genetic algorithm (GA), IEEE 34 nodes, mathematical optimization, iterations, minimization.

Resumen

Con la finalidad de enmendar perturbaciones como: caídas de voltaje, pérdidas de potencia, entre otros; debido a que las cargas en un sistema de distribución real son desbalanceadas y estas afectan la calidad y confiabilidad del servicio eléctrico. Se presenta una técnica de optimización matemática a través de un algoritmo genético, donde se plantea una función objetivo con el fin de minimizar pérdidas en el sistema. El objetivo del algoritmo genético es proporcionar la ubicación y dimensionamiento óptimo de un banco de capacitores en un sistema de distribución. Este método al ser iterativo busca la solución más factible mediante sus variables de población, generación, probabilidades de reproducción y mutación para cumplir con su función objetivo.

Palabras clave: algoritmo genético (GA), IEEE 34 nodos, optimización matemática, iteraciones, minimización.

Introduction

Electrical distribution systems often have disturbances that cause anomalies in the system such as voltage drops or energy losses, putting at risk the reliability and supply of electrical energy. Sanchez & Pascual (2021) indicate that for this reason, the implementation of components such as distributed generation or capacitor banks is of utmost importance to improve the efficiency and reliability of energy in the electrical system.

By optimally sizing and locating a capacitor bank in the electrical distribution system, it is possible to contribute to the reduction of active power losses, thus minimizing losses in the system.

(Simões & Ebecken, 2016) Therefore, in this paper, a heuristic optimization technique will be used, highlighted as a genetic algorithm that will allow finding a solution or set of solutions for the possible sizing and location of the capacitor bank. p. 10.

Lahoz, R. (2004); Ortiz-Quisbert et al., (2016) and Aguado & Cipriano (2009) mention that it is a systematic heuristic method for solving search and optimization problems that apply the same principles of biological evolution, selection based on a population, reproduction and mutation. Then, it is possible to solve the problems of finding the values of the parameters describing the shape model of the given function. In the genetic algorithm, each vector of parameters is called a "chromosome", and the set of all parameters that is analyzed to find the solution is called a "population". For Corso et al. (2016) states that intuitively see as a population of individuals (chromosomes) in which all compete to find the most act or the most suitable.

Ortega, Bravo & Ruiz (1997) and Blanco-Kelly et al. (2021) state that the genetic algorithm works as follows: in an optimization process by natural selection, it starts once an initial population of chromosomes has been randomly defined, and then evaluates the suitability (fitness) of each chromosome. If any of the chromosomes represents the optimal level, then the algorithm stops the search or exploration, and then terminates. Otherwise, for Salazar-Hornig

& Medina (2013), in the reproduction phase, the chromosomes that will be part of the next generation are selected in such a way that a higher probability in the reproduction rate is added to the best evaluated chromosomes. The whole process is repeated iteratively until the algorithm finds the ideal chromosome.

As mentioned by Arahal, Berenguel & Rodríguez (2006); Martí et al., (2014) and Figueroa et al. (2018) the genetic algorithm is inspired by Darwin's principle of evolution, this algorithm simulates this principle by evaluating chromosomes of a population. The objective function of the genetic algorithm is a mathematical function $f(x)$ that represents the chromosome evaluation function, providing a numerical value that is interpreted as the measure of fitness, i.e. the suitability of the chromosome against a problem space. Based on this, the objective function $f(x)$ will determine the evolutionary or adaptive surface over which the genetic algorithm will scale.

To do so, you must follow the following process:

- Time 0 ←
- Generation of initial population, P0
- Initial stock assessment P0
- As long as (no (completion condition))
- Home

time time + 1 ←;

Selection of the potential solution M_{time} from the previous population P_{time-1} ;

Modify the potential solution M_{time} using genetic operators;

Create a new population P_{time} from the potential solution M_{time} ;

Assessment of the current population, P_{time}

- End meanwhile;

For the optimization of a distribution network Gutierrez, G (2018) mentions that it is important to know the behavior of the power flow and losses in the line in order to be based on the optimization of losses in the distribution network, therefore, the equation in which the losses of a distribution network transmission line are defined is expressed as follows:

$$P_{Loss}(i,j) = R_{ij} \left[\frac{P_i^2 + Q_i^2}{|V_i|^2} \right] \quad (1)$$

Where:

R_{ij} : represents the resistance of line i-j.

P_i : represents the active power flow of line i-j.

Q_i : represents the reactive power flow of line i-j.

V_i : represents the voltage of bus i connecting line i-j.

Then the objective function is expressed as:

$$P_{Loss}(i, j) = \sum_{i=0}^{\#lines} P_{Loss}(i, j) \quad (2)$$

In the distribution system for the optimization of losses in the network, first we define the losses in the distribution line as shown in equation (1), with which we obtain the objective function in equation (2), which was raised for the resolution of the problem.

Once the optimization objectives are known, the following constraints are considered.

Subject to:

$$\sum Q_{cap} \leq \sum Q_{load} \quad (3)$$

$$V_{i \min} \leq V_i \leq V_{i \max} \quad (4)$$

$$P_{ij \min} \leq P_{ij} \leq P_{ij \max} \quad (5)$$

Soria, Pandolfi & Villagra (2013); Salazar-Hornig & Medina, (2013) define the recombination operator or also called Crossover as the most important search operator of the genetic algorithm, this has the function of exchanging the genetic material of a pair of parents producing successors that normally differ from their parents. On the other hand, Saltos, C (2000) mentions that the crossover probability (indicated by P_c) is the ratio between the number of children produced in each generation and the population size (indicated by pop_size), a high crossover probability allows a greater search of the solution space.

Soria, Pandolfi & Villagra (2013) and Toll et al. (2021) allude that there are three ways to do vector crossover such are:

One-point crossover - This technique was proposed by Holland and is the simplest crossover technique, but it is not widely used today because of its disadvantages. Once two individuals have been selected, their chromosomes are cut at a randomly selected point to generate two segments in each of them: the head and the tail. The tails are exchanged between the two individuals to generate new offspring.

Two-point crossover - Similar to the one-point crossover, the difference is that it generates two cut points instead of one, where it must be taken into account that none of these cut points coincide with the end of the chromosomes to ensure that three segments are originated.

Probabilistic crossover - The technique involves the generation of a crossover mask with binary values, if in one of the positions of the mask there is a 1, the gene located in that position in one of the offspring is a copy of the first parent, while if there is a 0 the gene is copied from the second parent. Saltos, C (2000) indicates that the mutation in a genetic algorithm is an operator that serves to reintroduce lost alleles (value of a gene), i.e. bit positions that converge to a certain value in a population for this reason in genetic algorithms the crossover is the most important search operator.

For his part Cuervo, R (2019) points out that the fitness function is a very important part in genetic algorithms, since it is the one that assesses how good an individual is, if in the evaluation the individual is good it will pass from generation to generation to achieve the objective of the algorithm.

There are two ways to optimize a process, which is maximization and minimization, where according to Amat, J (2019) the fitness function acts differently in both cases, as shown below.

In maximization, the individual will have a higher fitness when the objective function $f(\text{individual})$ is higher.

In minimization: in this case the individual will have a higher fitness the lower the value of the objective function, so for minimization problems it can be calculated by $-f(\text{individual})$ or $(1+f(\text{individual}))^{-1}$.

Materials and methods

For the development and obtaining of the results, the following research is considered non-experimental, because it consists only of a technical analysis of the optimization of the radial distribution system of the IEEE 34 nodes with the objective of minimizing power losses using the genetic algorithm. For the power loss reduction approach, the objective function to be minimized and the constraints are formulated; where the same variables will be evaluated for each iteration so that a solution outside the limits does not converge.

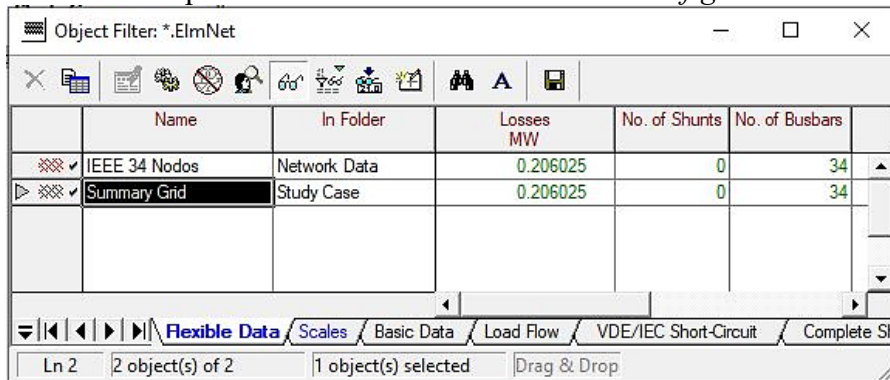
Then the matrices and vectors that will be used for storing the data of the heuristic algorithm will be defined and initialized, for which it will be necessary to obtain the objects of the nodes (**.ElmTerm*), load (**.ElmLod*), lines (**.ElmLne*), capacitor banks (**.ElmShnt*) and the system network (**.ElmNet*), using the *AllRelevant* command to obtain all the data of the specified object; for the location and optimal sizing of capacitor banks in the IEEE 34 node system is complementary the manipulation of the service states, such as the amount of reactive steps of the capacitor banks for which by means of the *AllRelevant* command (**.ElmShnt*) can be enabled and disabled according to the iteration and responses of the genetic algorithm;

taking into account that node 800 is not considered for the location of capacitor banks as it is a reference bus.

Once the active power losses are evaluated through the power flow by means of the *Load Flow Calculation (ComLdf)* command, in each iteration the different combinations of capacitor banks in the nodes evaluated by the genetic algorithm are performed, this should take the best value, therefore the system will present the best results of power flow, being these the best power conditions in the lines, these will be the values selected and stored in the *fitness vector* that represent the best solution that the GA will provide.

Result

Using the methodology in reference to the previous section. The number of population was defined to be 100, and a number of 100 iterations was defined. Once the 100 iterations were completed, the algorithm determined that it is necessary to use 7 capacitor banks. Considering that the losses before compensation were 206.025 KW shown in *figure 1*.



	Name	In Folder	Losses MW	No. of Shunts	No. of Busbars
✓	IEEE 34 Nodos	Network Data	0.206025	0	34
▶ ✓	Summary Grid	Study Case	0.206025	0	34

Figure 1. Grid-wide data after power flow without reactive compensation.

The solution obtained by the GA to minimize losses was 168.948 kW shown in *Figure 2*, thus reducing power losses by 18%, which in power is equivalent to 37.077 kW.

Name	In Folder	Losses MW	No. of Shunts	No. of Busbars
IEEE 34 Nodos	Network Data	0.168948	7	34
Summary Grid	Study Case	0.168948	7	34

Figure 2. Grid-wide data after power flow with reactive compensation.

Figure 3 shows the graph of the Fitness GA function going from the highest power obtained in the iterations to the one that was the solution proposed by the heuristic method.

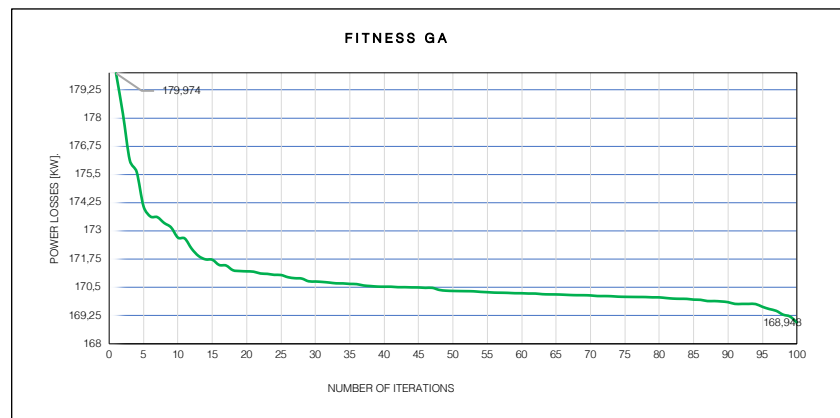


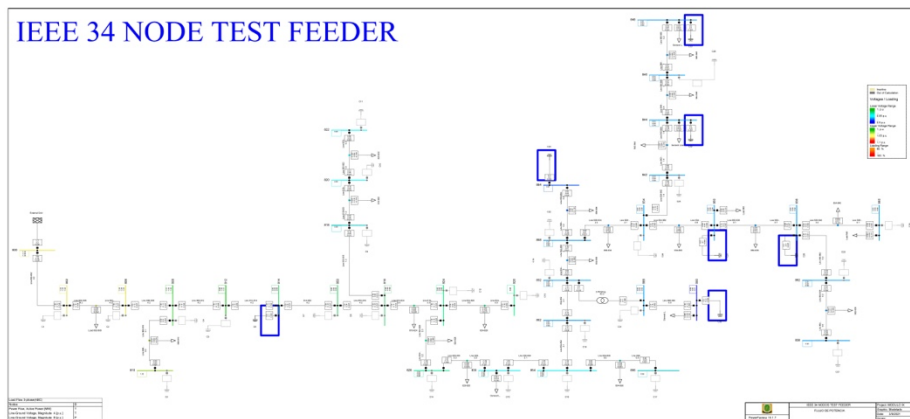
Figure 3. Graph of GA fitness function.

The capacitor banks to be used according to the GA will be located at nodes 814, 836, 844, 844, 848, 860, 864 and 890, as shown in Table 1, which also details the reactive power of each capacitor injected to the system, and the reactive steps of the capacitor banks being the maximum 30.

Figure 4 shows illustratively the location of the capacitor banks in service, marked with a blue box in the IEEE 34-node system, modeled in DIGSILENT PowerFactory software.

Table 1. *Optimal Capacitor Bank Location proposed by the GA*

Node	Capacitor	Power [MVar] [MVar]	Act. Step
864	C23	0.030	2
860	C27	0.090	6
836	C28	0.345	23
890	C30	0.060	4
844	C32	0.045	3
848	C33	0.135	9
814	C6	0.120	8
Total	7	0,825	

**Figure 4.** Location of capacitor banks that injected reactive power to the system.

Considering that the main objective function is to reduce losses in the system and it is not a multiobjective function, but reducing losses also improves the voltage profile of each phase as shown in *Figures 5, 6 and 7*, which represent the voltage per phase in per unit of each of the nodes of the distribution network.

The uncompensated system is shown in blue on the curve and the compensated system with the 7 capacitor banks is shown in red.

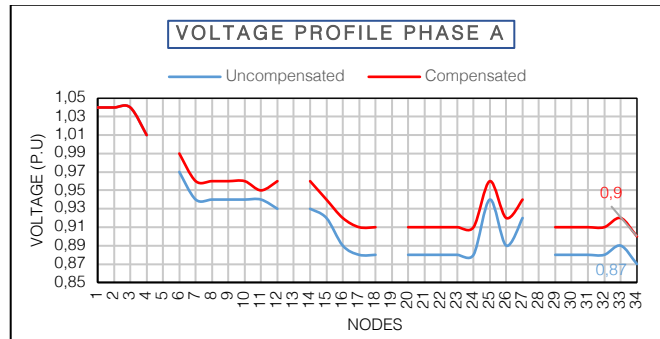


Figure 5. Voltage profile per node in phase A.

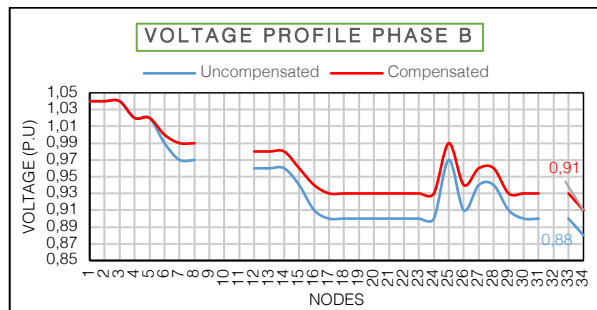


Figure 6. Voltage profile per node in phase B.

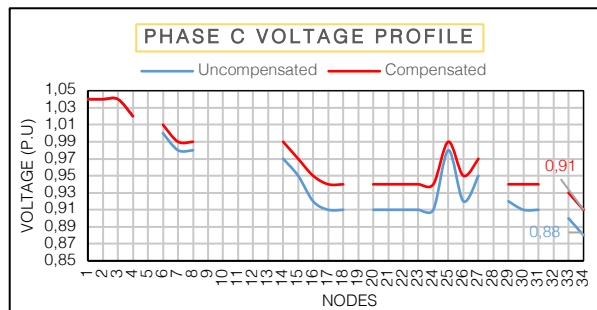


Figure 7. Voltage profile per node in phase C.

The approximate value when improving the voltage is 0.03 Pu as a maximum value in most of its nodes, such voltage profile values are within the restrictions.

To obtain a better validation of the method used, it would be to choose an alternative software for the development and comparison of the results or to perform the same procedure using another heuristic method.

Another factor to consider would be the execution of multi-objective functions to obtain the minimization of losses in addition to improving the voltage profile in the system as well as the power factor, thus obtaining more feasible and efficient results in the location and sizing of capacitor banks in a distribution system.

Conclusions

The implementation of the genetic algorithm yields the best solution of the system. For this purpose, the set of feasible solutions that limits the random search of the capacitor banks was proposed, this is detailed by means of a matrix where the node number and the reactive steps in each capacitor bank that predetermines the range of solutions are denoted. A preliminary analysis of the system should be performed so that the maximum capacity of the capacitor banks does not exceed the load capacity per node in the system.

The implementation of the genetic algorithm determines that the best solution for the 34-node IEEE system is the contribution of 7 capacitor banks with an injection of 825 kVar of reactive power to the system.

The algorithm solution was based on an objective function and constraints, opting for the best solution based on mutation and replications; the algorithm consists of 100 iterations, this being the population of the GA. Before implementing the algorithm the losses of the system were 206,025kw, optimizing the distribution system the losses in the network are 168,948kw this indicates that the system reduced the losses in total of 37,077 kw equivalent to a percentage of 18% of losses.

It is determined that the optimal sizing and placement of the capacitor bank in the IEEE 34 node system raises the voltage level in each of the phases, with a maximum value of 0.3 pu, which shows an improvement in the voltage profile.

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