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Power Loss Minimization by Voltage Transformer Turns Ratio Selection based on Particle Swarm Optimization

Abstract*. The research considers the optimization of the taps position of voltage transformers to minimize power loss. The Particle Swarm Optimization algorithm is implemented to this optimization problem. The advantage of this algorithm is the ability to adapt to an optimization problem. It was found out that the Particle Swarm Optimization algorithm is more productive than the greedy heuristic algorithm based on the division of this optimization problem into subtasks. Also, the paper studied the influence of particle velocity restriction on the efficiency of the algorithm.*

Streszczenie. *W pracy analizowano metode optymalizacji strat transformatora przez dobór stosunku uzwojeń. Do tego celu wykorzystano algorytm genetyczny PSO. Porównano prace układu z innymi algorytmami adaptacyjnymi.* ***Minimalizacja strat mocy w transformatorze przez dobór stosunku zwojów z wykorzystaniem algorytmu PSO***

Keywords: voltage transformer, active power loss, greedy heuristic, swarm intelligence, particle swarm optimization.
Słowa kluczowe: transformator, straty mocy, algorytm genetyczny PSO

Introduction

Power losses in electrical grids represent one of the essential indicators of effectiveness. The power losses in electrical grids are the difference between power generated by power plants and power consumed by customers. The losses occur in power transformer and power lines, especially when transmission energy over long distances.

Voltage control noted of power system it allows to solve the following main tasks [1, 2]:
- balancing between generation and consumption;
- providing the required voltage level at the terminals (outputs) of consumers of electric energy.

There is voltage regulation on the longitudinal and transverse directions. Providing the required level of voltage at the terminals of consumers of electric energy is solved mainly by longitudinal regulation [2, 3, 4].

The existing centralized management system prevents many active objects from appearing in the network. The basis in the centralized system is the control center, where the modes of operation of all control objects are determined [3, 5]. When a new object or a change in the desire of the subjects, it is necessary to reconfigure the system, which is a very time-consuming process.

The emergence of distributed means of voltage regulation in the network, belonging to different subjects, having their own goals of regulation, determines the need for a qualitatively new solution to the problem of voltage regulation in electric networks. It is necessary to develop new methods to control the modes of operation of power supply systems, including distributed generation. Currently, worldwide attention is paid to the creation of intelligent power supply networks (Smart Grid).

In high and medium voltage networks, there are large power flows, accompanied by significant losses. The problem of reducing power losses during transmission can be solved through transverse voltage regulation.

The problem of voltage regulation can be solved by adjusting the power factor of transformers in the network. Changing the position of the transformer taps does not require the installation of additional equipment, in contrast to using shunt capacitors for reactive power compensation.

Currently, the task of selecting the tap positions of transformers, as a rule, is solved by breaking the problem down into separate parts with the optimization of each of them [3, 4, 6], or using heuristics, often based on fuzzy logic [7, 8]. At the same time, for power systems, it is advisable to use optimization stochastic population-based algorithms, which can find quasi-optimal solutions in a reasonable time and, most importantly, to adapt to the conditions of the problems and the topology of the optimized systems [9-12]. In this paper, we compare deterministic methods such as greedy heuristics with a stochastic Particle Swarm Optimization (PSO) algorithm.

A fragment of Tajikistan's electric power system was chosen as a model for experiments. We consider the 17 most crucial transformers of the power system. All of these transformers have the ability to regulate the voltage by switching with 15 steps and a step between the coefficients 1.78. Information on network nodes is given in Table 1, information on transformers is given in Table 2.

The Optimization problem

$$Tr^{opt} = \arg\min_{1 \le Tr_i \le m,\, i=1,\dots,n} (\Delta P(Tr) + Stab(Tr)) \tag{1}$$

where: Tr – vector of the transformer tap positions, $\Delta P(Tr)$ – active power loss in the power system, $Stab(Tr)$ is a penalty function to check the stability of the power system, m – count of possible transformer tap positions, n – is count of transformers. It the power in question, n = 17, m = 15.

The Greedy Heuristics algorithm

The problem under consideration is a combinatorial optimization problem. The total number of possible solutions-combinations of the problem can be determined based on the number of adjustable transformers (17) and the number of possible positions of the transformer taps (15). The total number of combinations is 15^{17}, which is about 10^{20}. Obviously, it is impossible to apply a brute force as a full search of all possible combinations in practice. It is using of Branch and Bounds method or Simplex method also not suitable for this problem, because for the network in question requires a cumbersome system of differential equations, which is solved approximately. Also, this combinatorial problem belongs to the class of NP-complete, since it can be reduced to the SAT problem asks whether a given boolean formula is satisfiable. Therefore, the time required for its exact solution increases exponentially with the number of transformers.

It is necessary to apply a method that, firstly, would find a solution in an acceptable time, and secondly, would allow looking for solutions to the optimization problem, as a black box. The second requirement is due to the high complexity of the integration of optimization methods in mathematical models used for the calculation of power grid modes.

Table 1. Voltage, active and reactive power in the steady state

Id	Voltage nominal, kV	Active power, MW	Reactive power, MVAR
1	230	179.5	134.6
2	11	28	19.6
3	115	163	117.4
4	115	0	0
5	11	0	0
6	38	18.5	12.9
7	230	109	76.3
8	11	0	0
9	115	0	0
10	230	-459	-302.7
11	230	0	0
12	7	4	2.4
13	38	12	8.4
14	230	0	0
15	230	0	0
16	11	14	9.8
17	230	0	0
18	38	45	30.1
19	11	15	9.3
20	115	124	86.8
21	115	0	0
22	11	8.4	6.3
23	38	20	13.6
24	230	0	0
25	115	0	0
30	11	-70	-46.1
31	11	-60	-39.5
32	230	0	0
33	230	0	0
34	230	0	0
35	230	0	0
36	230	0	0
37	230	0	0
38	230	0	0
39	230	0	0
40	230	0	0
41	11	-70	-24.5
42	11	-70	-46.1
43	230	0	0
45	11	-60	-29.9
44	230	0	0
46	230	0	0
47	230	0	0
48	115	0	0
49	115	0	0
50	115	0	0
51	115	0	0

Table 2. Considered transformers

Id Transformer	High-voltage side node	Low-voltage side node
1	7	8
2	7	8
3	15	16
4	15	16
5	15	16
6	1	2
7	1	2
8	24	41
9	24	42
10	4	5
11	4	5
12	21	22
13	21	22
14	11	45
15	17	19
16	17	19
17	14	12

Simple in implementation, fast in calculations and at the same time providing some level of increase of energy efficiency of the system is the greedy heuristic (GH) [6]. It works as follows.

1. The current position of all adjustable transformers is set.
2. Let k – be the number of the considered transformer, start with $k = 1$.
3. If k does not exceed the number of transformers, go to step 4. Otherwise to step 6.
4. Calculate the steady state for all 15 possible positions of transformer tap k. The position at which the loss of active power in the network lines is the smallest is stored as the current position.
5. $k = k + 1$. Go to paragraph 3.
6. If there is no improvement in the target function in the implementation of steps 4 and 5, complete the work. Otherwise, go to step 2.

The algorithm performs a local search, going through all possible positions of each transformer in turn. In the case where the mutual influence of transformers is small, the algorithm can find the optimal or close to the optimal solution in 1-3 passes through all transformers [6]. However, otherwise, the efficiency of the method may be low due to falling into the same local extrema at each iteration. This drawback is inherent in other heuristic methods that optimize parts of the system separately [3].

In studies [6, 8], it is shown that this algorithm can be improved using Fibonacci numbers or Fuzzy logic. Fibonacci numbers approach reduces the time of the algorithm by reducing the iterated options. However, the quality of the resulting solutions remains the same as the GH algorithm. In this case, for the application of Fuzzy logic is associated with significant labor costs for the preparation of fuzzy input and output linguistic variables, and rules describing the choice of the positions of the tap in a given situation.

Therefore, in this paper, a direct experimental comparison of these methods is not carried out. For the experiments, the implementation simpler algorithm of the GH algorithm described above is chosen. Alternatively, an approach based on a completely different mechanism, namely the PSO algorithm, is considered.

The Particle Swarm Optimization algorithm

Greedy heuristic methods are characterized by high speed of work, but strongly depend on the topology of the problem, the initial approximation and heuristic rules. Therefore, the solution obtained by the greedy heuristic method can be both optimal and very far from optimal depending on the above factors. More complex and useful are stochastic algorithms of global optimization, such as the Genetic algorithm, the Simulated Annealing algorithm, the Swarm Intelligence algorithms. These stochastic meta-heuristics methods demonstrate high efficiency in terms of decision quality and calculation speed for various optimization problems in power systems (Simulated annealing [13], Genetic algorithm [10, 12, 14], Ant colony optimization [10], Bee algorithm [12], the most popular swarm algorithm is PSO).

The PSO algorithm as meta-heuristic method has high robustness and flexibility, it is realy important for optimzation complex and non-linear systems. The survey of meta-heuristic method [10] shows that PSO is fast and robustness method for for under voltage load shedding in power systems.

Numerous studies prove the effectiveness of the PSO algorithm in solving problems of reactive power compensation, and voltage control. The research [12] compares the Genetic algorithm, Bee algorithm and PSO algorithm in operation control of reactive power units. The

PSO algorithm is useful independently of reactive power source type and power system structure: integration D-STACTOM for radial systems [15], multi-objective capacitor allocation and sizing in distribution networks [16], all VAr sources management in power transmission system [17]. It can be applied for the optimal regulation capacity of the voltage regulating equipment at all times of a day to the optimization of load and loss reduction of distribution network [18]. The original method as a hybrid artificial neural network and PSO proposed in [19] to both optimizations of reactive power and voltage control.

The PSO algorithm is successfully applied in the other optimization problems, such as scheduling problems [20, 21], to represent distributed energy resources [22], the optimization size of distributed generation [23].The PSO algorithm was proposed by J. Kennedy and R. Eberhart, then improved these authors and Y. Shi to the version that is classical today and in subsequent years developed to one of the most popular and effective methods for solving optimization problems [24, 25]. It belongs to the class of Swarm Intelligence algorithms. The basis of the work of the swarm algorithms is the movement of agents-solutions to the problem in the multidimensional space of finding solutions with the indirect exchange of experience between them.

We present the optimization problem as the problem of finding the minimum of the function $f(X)$, where X is a vector of controlled variables. In this paper, the vector X specifies the number of tap regulated transformer network, and the function $f(X)$ determines the magnitude of the active power losses in branches of a network.

According to the scheme of the description of swarm algorithms proposed in [12], the PSO algorithm can be written as a tuple $\{S, M, A, P, I, O\}$. S refers to the set of agents of a swarm (particles); M means of indirect exchange of information between them; A is the rules of moving particles using heuristic parameters of the vector P. The elements I, O define input and output data flows when we implement the interface between the swarm algorithm and the problem to be solved.

Each swarm particle from S is characterized by a vector of coordinates X in the search space D and the value of the optimality criterion $f(X)$. The number of particles is s. Each particle has its variable velocity, vector V. Initially, the values of the elements of vectors X and V are chosen arbitrarily, $X \in D$ ($x_i \in [0, 1]$, $i = 1, \dots, d$), d – is the dimension of the search space. Then, at each step of the algorithm, the vectors X and V for each particle are updated according to the following formulas [12, 21]:

$$V \leftarrow V\omega + \alpha_1 (Pb - X) random(0,1) + \alpha_2 (M - X) random(0,1) \tag{2}$$

$$\begin{aligned} & if\ V_j > \beta\ \ then\ V_j = \beta, i = 1,...,n \\ & if\ V_j < -\beta\ \ then\ V_j = -\beta, i = 1,...,n \\ & X \leftarrow X + V \\ & if\ X_j > 1\ \ then\ X_j = 1, i = 1,...,n \\ & if\ X_j < 0\ \ then\ X_j = 0, i = 1,...,n \end{aligned} \tag{3}$$

where Pb is the position of the particle with the minimum (best) value $f(X)$ among all positions in which it was,

M – position, similar to Pb, but for all swarm particles that is the best position among all tested,

random(0, 1) is a vector of random numbers uniformly distributed from 0 to 1 (random vectors are generated for each iteration and each particle). The dimensions of the vectors are equal to the dimensions of the solution search space. Eq. (2) implies the element-by-element multiplication of vector components.

The parameters α_1 and α_2 determine the degree of attraction of the particle to the individual best position Pb and the overall best position M. The parameter ω characterizes the inertia of the particles. Parameter β is a new parameter of the algorithm along with α_1, α_2, ω, it restricts the velocities of particles. Thus, the parameter vector P consists of $\{\alpha_1, \alpha_2, \omega, \beta\}$. In the classic version of PSO parameter β missing as a parameter, that is always equal to one. Speed limit reduces the risk of missing the global optimum without complicating the algorithm.

To implement the PSO algorithm to optimisation problem (1) we need to:

- convert particle position X in Eq. (2), (3) to vector Tr in Eq. (1);
- convert criterion value $\Delta P(Tr)$ + $Stab(Tr)$ in Eq. (1) to $f(X)$.

It can be done as follows:

$$\begin{aligned} & Tr_i = \lfloor mX_i \rfloor + 1, i = 1,...,n \\ & f(X) = \Delta P(Tr) + Stab(Tr) \end{aligned} \tag{4}$$

If the simulation of the power system shows that the system mode is unstable, then the penalty function $Stab(Tr)$ gets a value that is antecedently higher than the possible value of the power loss $\Delta P(Tr)$. Otherwise, it gets zero. So, solutions that lead to unstable mode will be much worse by the criterion $f(X)$.

Experimental comparison of the algorithms

The GH algorithm was performed from the first transformer to the 17th, and then from the 17th to the first. Two runs were performed to demonstrate the dependence of the method on the initial approximation.

The disadvantage of the PSO algorithm is the dependence on the values of the parameters used $\{\alpha_1, \alpha_2, \omega, \beta\}$. In this case, it is theoretically impossible to choose universal values that are effective for all tasks. It is confirmed by practice [21, 26], and has a justification according to the No-Free-Lunch theorem [27]. Several sets of parameters recommended for a wide class of problems were taken for the PSO algorithm [21, 25, 26]:

α_1 = 1.5, α_2 = 1.5, ω = 0.7, β = 0.1,
α_1 = 1.5, α_2 = 1.5, ω = 0.7, β = 0.3,
α_1 = 1.5, α_2 = 1.5, ω = 0.7, β = 1.0.

The differences in β values are explained by the fact that for the parameters α_1 = 1.5, α_2 = 1.5, ω = 0.7 good efficiencies can be obtained without speed restriction. At the same time, the restriction should theoretically improve the quality of the obtained solutions, so the value 0.3 is taken, which showed high efficiency in the study [21] and the value 0.1 since a further decrease in the maximum speed can negatively affect the ability of the algorithm to exit local extrema. The number of particles was chosen to be 50 and the number of iterations 50 and 500.

The experimental results for the model of the considered power supply network are given in Table 3 and Fig. 1.

Each line $Id_{tap\ i}$ (i = 1, …, 17) contains the position tap of i-th transformer recommended by an algorithm. The line "Losses, MW" contains active power losses in the lines of the power system. The line "Effect, MW" shows how much loss decreased as a result of the optimization by an algorithm.

Table 3. Comparison of the solutions of the algorithms

Algorithm	Current position	GH 1-17	GH 17-1	PSO 50 steps, β = 0.1	**PSO 500 steps, β = 0.1**	**PSO 50 steps, β = 0.3**	**PSO 500 steps, β = 0.3**	PSO 50 steps, β = 1.0	PSO 500 steps, β = 1.0
Losses, MW	48.01	46.32	47.28	46.08	**45.90**	**45.88**	**45.83**	46.23	46.21
Effect, MW	0	1.69	0.73	1.93	**2.11**	**2.13**	**2.18**	1.78	1.80
Id_{tap} 1	2	11	2	9	**10**	**10**	**8**	11	10
Id_{tap} 2	2	6	2	9	**8**	**10**	**8**	8	8
Id_{tap} 3	6	10	6	11	**12**	**14**	**10**	12	11
Id_{tap} 4	6	7	11	8	**11**	**14**	**10**	12	16
Id_{tap} 5	6	10	10	10	**12**	**14**	**10**	12	10
Id_{tap} 6	6	6	6	9	**10**	**9**	**8**	7	5
Id_{tap} 7	6	6	6	8	**9**	**8**	**7**	8	16
Id_{tap} 8	6	7	10	10	**10**	**12**	**10**	10	11
Id_{tap} 9	6	10	7	10	**11**	**8**	**10**	7	11
Id_{tap} 10	2	2	2	6	**10**	**4**	**9**	9	8
Id_{tap} 11	2	2	2	9	**10**	**4**	**7**	9	10
Id_{tap} 12	6	6	6	8	**7**	**8**	**9**	2	10
Id_{tap} 13	6	6	6	10	**7**	**8**	**8**	2	10
Id_{tap} 14	6	10	6	11	**12**	**6**	**10**	7	10
Id_{tap} 15	6	7	4	6	**10**	**4**	**6**	8	16
Id_{tap} 16	6	6	5	7	**10**	**4**	**16**	7	8
Id_{tap} 17	6	12	12	8	**8**	**11**	**4**	2	16
Average Id_{tap}	5	7	6	9	**10**	**9**	**9**	8	11

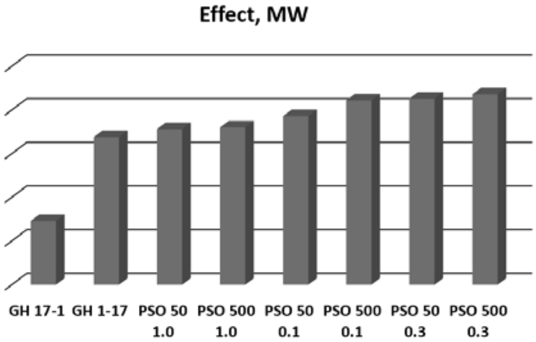

Fig.1. Comparison of the effects of the algorithms

Since the GH algorithm performed for the first time starting with the first transformer, then the second with the seventeenth, the results are given in two different columns (GH 1-17, GH 17-1, respectively).

For the PSO algorithm Table 3 shows the number of steps of the algorithm and the value of the various parameter β that restricting particle velocities.

The GH algorithm converged after four rounds of all transformers. The obtained differences in the results of one algorithm show how much the GH, like any greedy heuristic algorithm, depends on factors that are not directly related to the problem.

It is due to the algorithm falling into various local extrema, depending on the order of traversal of controlled variables. It is seen that the effect of optimization changes 2.3 times in different directions of search. However, even such a simple optimization method can save a significant amount of power at no cost other than creating a network model for its calculations.

The PSO algorithm has shown higher efficiency than is directed too much in only 50 iterations.

It should be noted that experiments with 50 and 500 iterations were performed as two different runs. Without limiting the maximum speed, the efficiency of the PSO algorithm is significantly lower, and the choice of the parameter β value equal to 0.3 gave the best results. It can be concluded that without limiting the maximum speed (β = 1.0), particles often "fly" past the neighborhood of the most effective extrema, and even once in them, can by inertia go back. In this case, too much speed limit (β = 0.1) worsens the search time of the effective solutions, hence the significant difference in solutions at 50 and 500 iterations.

Conclusion

The best solution to reduce the loss of active power in the system is achieved using the swarm Intelligence algorithm. When optimized using the swarm intelligence method in the network under consideration, it is possible to reduce the active power loss from 48.01 MW to 45.83 MW, i.e., by 2.18 MW or 4.5%.

In the best solution, the average position of the transformer tap was equal to 9. Although, a priori it could be assumed that this value should be close to the maximum value of 16 since the loss of active power decreases with increasing voltage. This assumption can be valid for radial networks in which mutual influences of different network segments are weak. For the considered non-radial network, this assumption is refuted by the experiment. It is shown that the application of the PSO algorithm is more efficient and easier to implement than the greedy heuristic algorithm. The PSO algorithm provides satisfactory solutions without setting parameters. Nevertheless, it is shown that the correct choice of the restriction of the particle velocity can give an additional quality increasing.

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