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Optimisation of low voltage network operation – selected power quality indicators vs. metaheuristic optimisation algorithms

Optymalizacja pracy sieci niskiego napięcia – wybrane wskaźniki jakości zasilania vs metaheurystyczne algorytmy optymalizacji

***Abstract**. The article analyses selected power quality indicators in a low-voltage network containing RES sources and energy storage. Their optimal values were determined using ten different metaheuristic optimisation methods. The proposed analyses will enable the selection of the most beneficial indicator from the point of view of managing the operation of the distribution network through optimal control of the charging power of energy storage and the reactive power of prosumer photovoltaic installations. This will also reduce power losses and equalise voltage profiles.*

***Streszczenie.** W artykule przeanalizowano wybrane wskaźniki jakości zasilania w sieci niskiego napięcia zawierającej źródła OZE oraz magazyny energii. Wyznaczono ich optymalne wartości przy wykorzystaniu dziesięciu różnych metaheurystycznych metod optymalizacji. Proponowane analizy umożliwią wybór najbardziej korzystnego wskaźnika z punktu widzenia zarządzania pracą sieci dystrybucyjnej poprzez optymalne sterowanie mocą ładowania magazynów energii oraz mocą bierną prosumenckich instalacji fotowoltaicznych. Pozwoli to również ograniczyć straty mocy i wyrównać profile napięcia.*

Keywords: power quality indicators, power losses, RES, metaheuristics.
Słowa kluczowe: wskaźniki jakości zasilania, straty mocy, OZE, metaheurystyka.

Introduction

The increase in the number of renewable energy source installations connected to the low-voltage distribution network may contribute to the deterioration of the operating conditions of the power grid. One relatively common problem is the increase in the voltage value in nodes above the permissible value. The second problem is the increase in power losses, especially in heavily loaded sections. To minimise the impact of the above phenomena on the operation of the network, energy storage devices installed in receiving or main nodes, the possibility of changing transformer taps, as well as photovoltaic installations enabling reactive power control can be used. This article presents the possibilities offered by the regulation of the above parameters in combination with optimisation methods. To compare the performance of individual methods and the selection of the values of the regulated parameters, it is necessary to formulate an objective function whose minimum will correspond to the best parameters of the network operation under the given assumptions. Properly selected indicators allow for the optimal equalisation of the voltage profile in the considered line string and the minimisation of power losses. The work is organised in such a way that the first two points contain an introduction to the analysed problem. The third section is a review of the determinants used in the literature to determine the optimal operation of the network in terms of active power losses and voltage values in the nodes. The fourth section presents a short description of the metaheuristic methods used for optimisation. The fifth section describes the test network. Finally, the simulation results are presented, as well as a summary and conclusions.

Literature review

Existing low and medium voltage distribution networks were designed as receiving networks, i.e. the power flow took place from the transformer station towards the recipients. For several years, with the increase in the number of RES sources connected and connected to the network, the situation has changed. Periodic power flows towards the transformer station are observed. High, periodic generation in renewable energy sources also contributes to the increase in voltage, which sometimes exceeds the permissible value, equal to 1.1 U_n.

In the available literature there are various methods and studies on methods of controlling network operating parameters. They include both conventional solutions used for many years, as well as those using the dynamically developing machine learning technology [1]. In [1], the authors also considered the use of one central energy storage or two energy storages in the depth of the network, aimed at eliminating voltage and balance problems in the low-voltage network. In order to maintain the required supply voltage values, regulation using transformer taps is often used in practice [2]. However, such a solution may prove insufficient, especially in wide-area networks saturated with a large number of renewable installations. It is therefore necessary to reach for other methods that allow for the effective elimination of the above-mentioned problem.

One solution for extensive networks may be to invest in additional devices such as voltage stabilisers [3], which are designed to counteract excessive voltage changes in the line. However, this is an expensive solution, which is its disadvantage. Another option is to use energy storage devices, which will allow to stabilise the voltage value in the vicinity of their installation point to a certain extent, and will also enable more efficient use of the power generated in renewable installations. The use of modern solutions and algorithms makes it possible to manage the operation of the storage device in such a way that it is charged only (or to a greater extent) from phases in which the required voltage value is exceeded [4].

Voltage regulation in the nodes of the distribution network can also be achieved by changing the flow of reactive power and the changes in voltage values caused by it. The reactive power required for voltage regulation can be obtained by using successively switched on batteries of chokes or capacitors, but one must take into account the abrupt characteristics of this solution. The capabilities of the controllers described in the literature [5] are also limited by the number of available batteries, so for most of the time moments the set reactive power may differ from the required one.

Another method is to change the reactive power of the inverters to which the RES installations are connected [6]. In the case of prosumer installations, changing the generated reactive power continuously makes it possible to make it dependent on the operating conditions of the source or the network. The characteristics for the reactive power of the inverter described in [7] assume independent operation for the connected distributed generation installations. The considered case of managing the reactive power of the inverters makes it possible to react more precisely to voltage changes in the line. Depending on the requirements of the network operator, the reactive power management is limited by the required $tg\varphi$ coefficient, failure to meet which may result in financial penalties.

Selected network performance quality indicators

This article analyses selected power quality indicators found in the literature. The aim of these studies was to find the most beneficial indicator from the point of view of optimising the operation of the power grid. Some indicators depend on the voltage value in the nodes or active power losses, while others take into account both of the above-mentioned values simultaneously.

The voltage values in individual nodes of the network, saturated with RES sources, can reach values higher than the allowable ones, especially in high generation conditions. The first indicator considered, based on sources [8] and [9], is the algebraic sum of relative deviations of voltage values in network nodes from the nominal value:

(1) $$\text{Ind1: } F_{obj}\left(\boldsymbol{x}\right) = \sum_{i=1}^{N} \frac{U_i - U_n}{U_n}$$

where: N – number of nodes in the network, U_i – voltage value in the node in relative units, U_n – nominal voltage value in the node.

Among the devices particularly sensitive to voltage deviations we can mention induction motors, whose generated torque depends on the square of the supply voltage. Due to the multitude of applications of this type of machines, the costs caused by the reduction of the efficiency of motors due to voltage deviations can become a significant problem [10]. This was one of the reasons for determining, in accordance with studies [11] and [12], another objective function as the sum of the squares of relative deviations of the voltage values in nodes from the rated value:

(2) $$\text{Ind2: } F_{obj}\left(\boldsymbol{x}\right) = \sum_{i=1}^{N} \left(\frac{U_i - U_n}{U_n} \right)^2$$

In order to generalise the index value and make it independent of the number of nodes in the considered network, the coefficient defined by formula 3 described in the literature [13] was introduced. It corresponds to the percentage value of the standard deviation of the voltage in nodes from the rated value, independent of the number of nodes.

(3) $$\text{Ind3: } F_{obj}\left(\boldsymbol{x}\right) = \sqrt{\frac{1}{N} \cdot \sum_{i=1}^{N} \left(\frac{U_i - U_n}{U_n} \right)^2}$$

Another issue related to the optimisation of system operating parameters are economic aspects directly related to the operation of distribution networks. The fourth objective function (formula 4), appearing among others in [14], corresponds to the total active power losses occurring during the operation of power systems, resulting in increased costs of electricity transmission.

(4) $$\text{Ind4: } F_{obj}\left(\boldsymbol{x}\right) = \Delta P$$

where: ΔP – total power losses in the network.

In order to determine the optimal operating state of network elements, both in terms of voltage deviations and active power losses, the weighting function described in [13] can be used. For the function described by formula 5, the coefficients α and β are selected in such a way as to bring both components to a comparable value. The calculations used relative power losses calculated in relation to the total power of the loads (formula 6) and the coefficient of the voltage deviation value in the nodes (formula 7).

(5) $$\text{Ind5: } F_{obj}\left(\boldsymbol{x}\right) = \alpha \cdot dP_{loss} + \beta \cdot U_{dev}$$

where: dP_{loss} – relative power losses, U_{dev} – coefficient of the standard deviation of the voltage in nodes.

(6) $$dP_{loss} = \frac{P_g - P_{ld}}{P_{ld}}$$

where: P_g – total power generated in the network, P_{ld} – total power drawn from the network.

(7) $$U_{dev} = \sqrt{\frac{1}{N} \cdot \sum_{i=1}^{N} \left(\frac{U_i - U_n}{U_n} \right)^2}$$

As the last function, in accordance with the formula described in [15], the relationship taking into account the relative active power losses calculated in relation to the total power of the loads and the coefficient of the standard deviation of the voltage in the nodes was used. This relationship is expressed by the formula:

(8) $$\text{Ind6: } F_{obj}\left(\boldsymbol{x}\right) = \sqrt{P_{loss}{}^2 + U_{dev}{}^2}$$

In contrast to formula (5), relation (8) does not contain weights for individual components. This way, their determination is avoided.

Metaheuristic methods

The use of classical optimisation methods works best in cases where the form of the objective function is known and it has one minimum. When the derivative of the objective function (or even its shape) cannot be unambiguously determined, there are many optima or there is a possibility of a divergent iterative process, it is inevitable to look for other optimisation methods. Metaheuristic methods may be a solution. They do not require knowledge of the derivative of the objective function and are resistant to discontinuities and stopping at a local minimum. A divergent iterative process is also not a threat to the entire process, because even if it occurs, there is no need to start the calculations from the beginning. In the context of the electricity system, constraints stem from the requirements of the network operator. These requirements include the need to consider emergency shutdowns (referred to as the N-1 analysis) and the necessity to ensure that the power balance is met. Failure to meet these requirements results in the imposition of a penalty on the result. In this way (if a global optimum exists), during the calculations, the solution will be found within the function domain defined by the constraints. This article compares the results of calculations obtained using ten different, effective metaheuristic algorithms describing animal behaviour. They were created and published by different researchers over the last dozen or so years. A comprehensive review of metaheuristic algorithms can be found, among others, in [16]. Analyses were performed based on the following metaheuristic algorithms: CS (Cuckoo Search) [17], GWO (Grey Wolf Optimisation) [18], PSO (Particle Swarm

Optimisation) [19], MFO (Moth-Flame Optimisation) [20], WOA (Whale Optimisation Algorithm) [21], FOX (FOX-inspired optimisation algorithm) [22], WHO (Wild Horse Optimiser) [23], GGO (Greylag Goose Optimisation) [24], WO (Walrus Optimiser) [25] and EHO (Elk Herd Optimiser) [26].

ELVTF test network

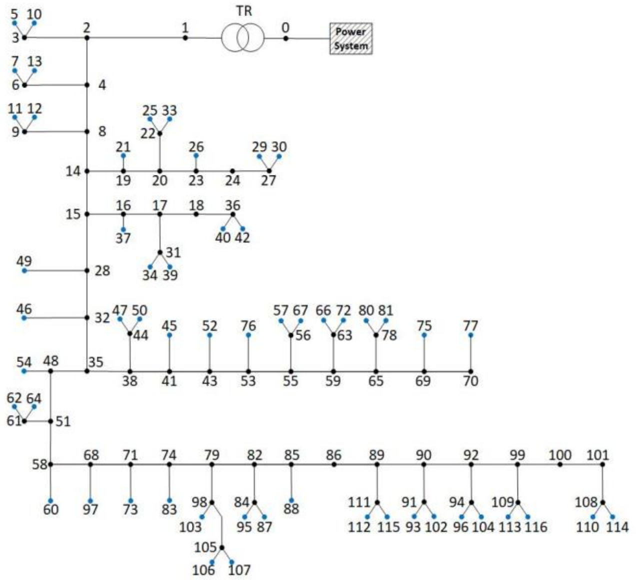

Fig. 1. Modified IEEE ELVTF (European Low Voltage Test Feeder) test network [27]

The modified IEEE ELVTF (European Low Voltage Test Feeder) test network described in [27] was used for the tests. The parameters of the individual elements of the network shown in Figure 1 were adapted to the parameters of the Polish power grid. The voltage levels were changed to 15 kV and 0.4 kV, and the line sections were modelled using commonly used wire cross-sections, i.e. 70 mm^2, 50 mm^2, 35 mm^2 in the case of overhead lines. The transformer used in the test network was replaced with a 250 kVA transformer with an installed tap regulator enabling automatic regulation. The load and generation in individual nodes were also changed. It was assumed that each of the receiving nodes (marked in blue in the figure) had a receiver with randomly selected active power. In selected nodes (12, 21, 26, 30, 34, 39, 42, 46, 49, 50, 54, 60, 64, 67, 72, 75, 77, 81, 87, 93, 96, 102, 104, 107, 110, 113, 115), constituting half of all receiving nodes, it was assumed that photovoltaic sources with maximum power of 10 kW each would be connected. Energy storage with the power of 10 kW installed at the recipients in nodes 29, 60, 66, 110 and 112, as well as a network storage with the power of 100 kW connected in node 86, were also added. The analysed low voltage test network thus corresponds to the specificity of the Polish network and shows one of the current problems faced by operators.

Calculation results

For the calculation purposes, the values of the loads in the nodes and the generation of photovoltaic sources were drawn, meeting the assumptions regarding the total network load of 90 kW and the total generated active power of 230 kW. For the charging power of energy storages, a restriction was imposed that did not allow their total charging power to exceed the value of the power generated by the PV installations. This avoided the case of power consumption from the medium voltage network in conditions of high generation in sources and the prevailing value of the charging power of energy storages.

Figure 2 presents graphs of the objective function dependent on individual, regulated quantities. They serve only to illustrate the shape of the function and the fact that the minimum occurs. When making them, in order to take into

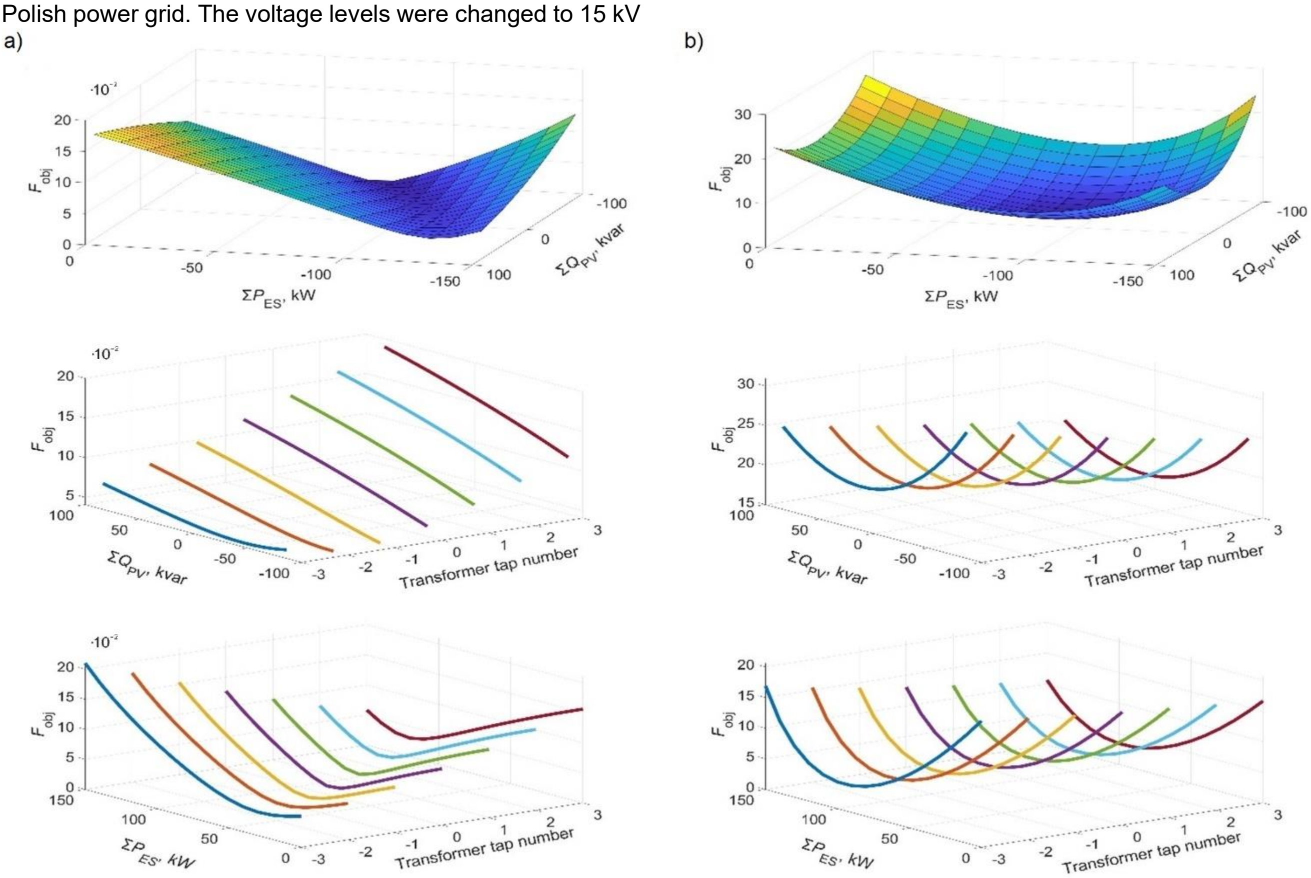

Fig. 2. Theoretical graphs of the objective function value equal to the third (a) and fourth (b) indicators for changes in the total reactive power of photovoltaic installations, the total charging power of storage facilities and the position of the tap changer in the transformer.

account the relatively large scope of the function domain, adding a penalty to the objective function related to failure to meet constraints was excluded. Graphs for indicators corresponding to the values of the relative voltage deviation coefficients in nodes, described by formula 3, and total active power losses in the network, described by formula 4, were selected for presentation. These indicators represent two different objective functions, containing different quantities.

The values of reactive power of photovoltaic sources and the values of power consumed by energy storage devices determined in the Matlab program (using successive metaheuristic methods) were sent in each iteration to the PowerFactory program, in which the flow analysis was performed. The results obtained during the analysis were used to find the optimal settings for the above-mentioned quantities, depending on the selected objective function. The cooperation of two computer programs, enabling the performance of various calculations, allowed for increasing the effectiveness and efficiency of the entire calculation.

The values of the objective function presented in Table 1 correspond to the lowest values of the indicators that were achieved during calculations for the individual methods. Tables 2 and 3 present the values of the relative power loss coefficients and the standard deviation of the voltage in the nodes for the results obtained in the subsequent cases. The values of the voltages in the network nodes (Fig. 4 and Fig. 6), as well as the values of the objective function in the subsequent iterations (Fig. 5 and Fig. 7) for the example indicators are presented below together with a legend explaining the colours of the markings used (Fig. 3).

Tab. 1. Values of the considered objective functions

Method	Ind 1	Ind 2	Ind 3	Ind 4	Ind 5	Ind 6
CS	1,3442	0,0142	0,0138	2,8470	0,0258	0,0381
MFO	1,2117	0,0173	0,0133	2,8451	0,0258	0,0448
WOA	0,6492	0,0367	0,0166	3,1260	0,0305	0,0394
FOX	1,5164	0,0295	0,0147	2,8447	0,0262	0,0382
PSO	0,9033	0,0115	0,0097	2,8214	0,0256	0,0378
WHO	0,7600	0,0064	0,0078	2,8320	0,0256	0,0379
GGO	2,0833	0,0464	0,0171	3,1717	0,0292	0,0429
WO	1,6550	0,0271	0,0136	2,8785	0,0258	0,0520
EHO	1,4897	0,0191	0,0138	2,8532	0,0266	0,0384
GWO	1,4143	0,0200	0,0133	2,9355	0,0328	0,0479

Tab. 2. Relative values of active power losses

Method	Ind 1	Ind 2	Ind 3	Ind 4	Ind 5	Ind 6
CS	0,0496	0,0575	0,0457	0,0317	0,0345	0,0331
MFO	0,0528	0,0525	0,0486	0,0317	0,0348	0,0417
WOA	0,1327	0,0556	0,0503	0,0348	0,0458	0,0342
FOX	0,0409	0,0381	0,0402	0,0317	0,0351	0,0337
PSO	0,0741	0,0776	0,0613	0,0314	0,0344	0,0329
WHO	0,1042	0,1125	0,0965	0,0315	0,0345	0,0330
GGO	0,0338	0,0395	0,0406	0,0353	0,0383	0,0369
WO	0,0542	0,0436	0,0496	0,0320	0,0347	0,0497
EHO	0,0548	0,0581	0,0516	0,0318	0,0361	0,0337
GWO	0,0524	0,0512	0,0517	0,0327	0,0493	0,0446

Tab. 3. Voltage coefficient values

Method	Ind 1	Ind 2	Ind 3	Ind 4	Ind 5	Ind 6
CS	0,0130	0,0110	0,0138	0,0245	0,0170	0,0188
MFO	0,0127	0,0122	0,0133	0,0264	0,0168	0,0163
WOA	0,0070	0,0177	0,0166	0,0209	0,0153	0,0195
FOX	0,0156	0,0159	0,0147	0,0252	0,0172	0,0181
PSO	0,0095	0,0099	0,0097	0,0260	0,0168	0,0186
WHO	0,0080	0,0074	0,0078	0,0262	0,0168	0,0187
GGO	0,0210	0,0199	0,0171	0,0266	0,0201	0,0219
WO	0,0189	0,0152	0,0136	0,0259	0,0169	0,0153
EHO	0,0163	0,0128	0,0138	0,0257	0,0171	0,0184
GWO	0,0150	0,0131	0,0133	0,0288	0,0163	0,0173

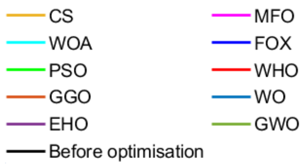

Fig. 3. Colour codes in charts

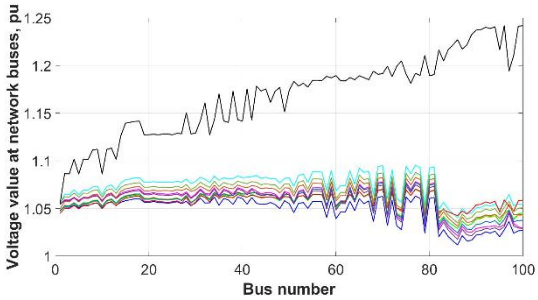

Fig. 4. Graph of voltage values in nodes for Wsk3

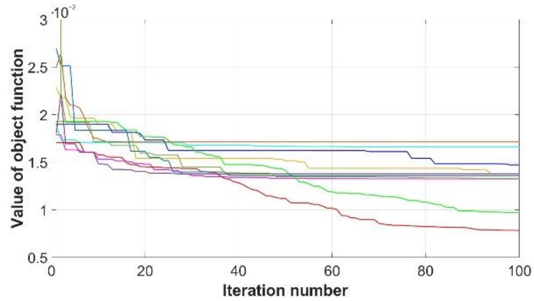

Fig. 5. Graph of the function value for Wsk3

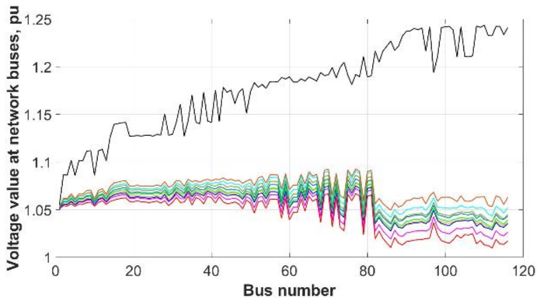

Fig. 6. Graph of voltage values in nodes for Wsk4

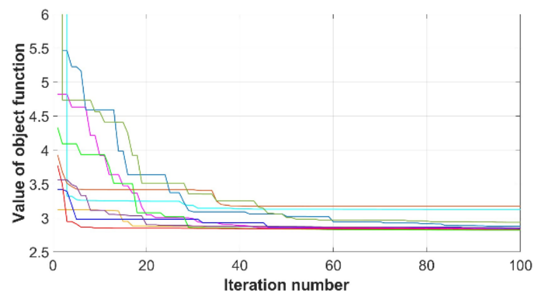

Fig. 7. Graph of the function value for Wsk4

The number of iterations and so-called agents was assumed to be the same for each analysed algorithm and equal to 100 and 10, respectively. Despite this, the optimisation time varied depending on the metaheuristic method. The average time from all studies was 9 minutes and 40 seconds, but the median was 6 minutes and 32 seconds per method. The algorithms for which optimisation took almost three times longer than for most of the others were WHO and EHO. The deviation from the average time for them was about 9.5 minutes, while from the median about

12.5 minutes. It should be noted that some optimisation algorithms, during one iteration, differentiate the decision variables twice or even three times, which extends the computation time but at the same time increases the effectiveness. This should be borne in mind when comparing different metaheuristic methods. It may turn out that performing one iteration by one algorithm comes down to determining the objective function twice or even three times, while in most other algorithms it is only a single calculation. This affects the efficiency and time to obtain the solution.

It can be seen that each method differs in the number of iterations after which it approaches the global minimum of the selected objective function, as well as in the voltage values in the network nodes that were achieved. Based on the obtained results, it can be stated that the method that achieves the lowest values of the objective function for most indicators is Wild Horse Optimiser (WHO). It usually approaches the minimum after about 60 iterations and achieves satisfactory voltage values in the nodes. For some methods, such as Greylag Goose Optimisation (GGO), during the initial iterations there were significant exceedances of the permissible voltages in the nodes or line currents. This resulted in adding a penalty to the value of the objective function.

Figure 8 presents a comparison of the values of the indicators for the WHO method. The choice of this method results from its greatest effectiveness in solving the problem considered in this article. Analysing the values of relative power losses in the network, related to its operating costs, the best value was achieved using indicator 4. Regardless of the applied metaheuristic method, the voltages for the objective function corresponding to the active power losses in the network were increased, which resulted in higher values of the voltage coefficient. The aforementioned coefficient corresponding to the value of voltages in nodes achieved the lowest values for the application of the objective function equal to indicator 1 (formula 1). In general, it can be said that the objective functions containing only the voltage indicator are characterized by the fact that the power losses in the network, in the optimal state, are greater than in the case of, for example, indicator 4, which minimizes them. Indicators taking into account both voltage deviations and power losses constitute a compromise between the optimal equalisation of the voltage profile and optimal power losses in the network. Looking at the quite significant differences in the values of power losses, the choice of the mixed indicator seems to be reasonable and rational. Which of these two goals prevails is decided by appropriately selected weights (indicator 5). Depending on the importance of each of them, the user should select the appropriate weights.

When analyzing the values of reactive power of sources obtained as a result of optimisation, presented in Figure 11, it can be noticed that the highest values of reactive power consumed in individual sources are observed for the second indicator. The highest use of the regulation capabilities of photovoltaic sources, corresponding to the highest total reactive value of sources, was observed for indicator 1 and the WHO method. The calculation results regarding the minimisation of active power losses in the network, for most metaheuristic methods, indicate the advantage of reactive power generated in sources over the power consumed. This is consistent with the observation of the increase in voltage in nodes for the aforementioned objective function. Looking at the values of the charging power of individual storages for the subsequent objective functions, it can be seen that the first three achieve the maximum possible charging power for all cases, while the charging powers of storages in nodes 110 and 112 differ for individual indicators (Fig. 9). This may indicate that more effective optimisation for controlling the reactive power of sources took place then. Considering the values of the charging power of the network storage installed in node 86 (Fig. 10), it can be seen that it takes values from fifty to seventy percent of the maximum power. This means that it was possible to reduce the investment costs by installing a storage with lower power.

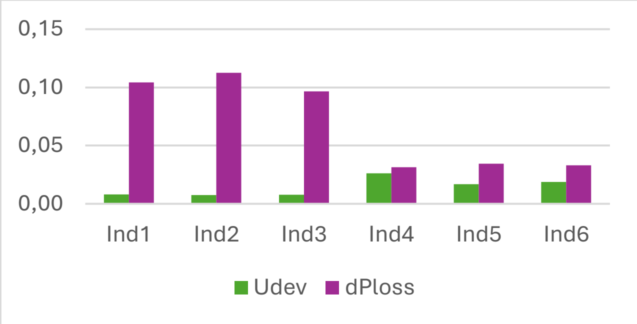

Fig. 8. Comparison chart of voltage coefficient values and relative power losses using the WHO method

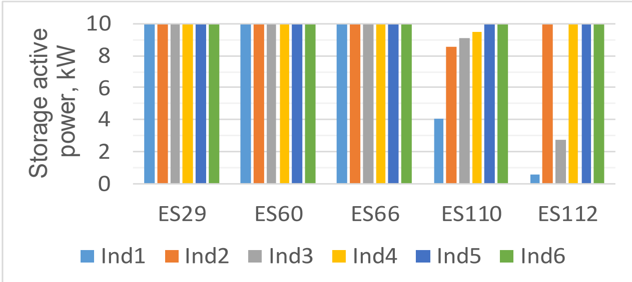

Fig. 9. The values of power consumed by prosumer storage facilities, for the following indicators, using the WHO method

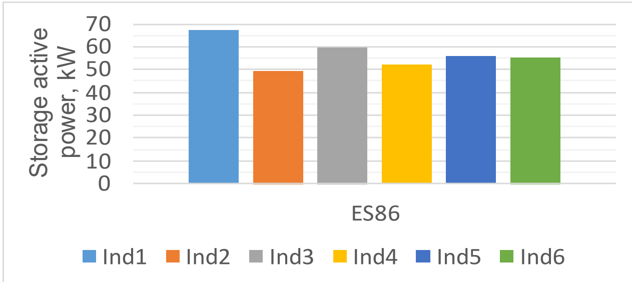

Fig. 10. Power values consumed by the network storage, for subsequent indicators, using the WHO algorithm

Summary

Deviations in the voltage supplying prosumer installations may result in limiting the power generated by PV sources, disruptions in the operation of devices or a decrease in their efficiency. Increased active power losses caused by a non-optimal network operating point are also undesirable due to the increase in network operating costs. The optimisation methods and objective functions proposed in this article, in relation to which the values of reactive power of sources and storage charging power were adjusted, allow for more effective introduction of power generated in prosumer installations to the network and limiting the exceedances that occur. The proposed methodology would allow for managing the operation of inverters included in the installations, as well as more precise selection and control of the power of energy storages. Using energy storages to collect excess power generated by RES and to optimize the voltage values in the network allows not only to control the voltage profile or power losses, but also to maximise the profit associated with the operation of the storage.

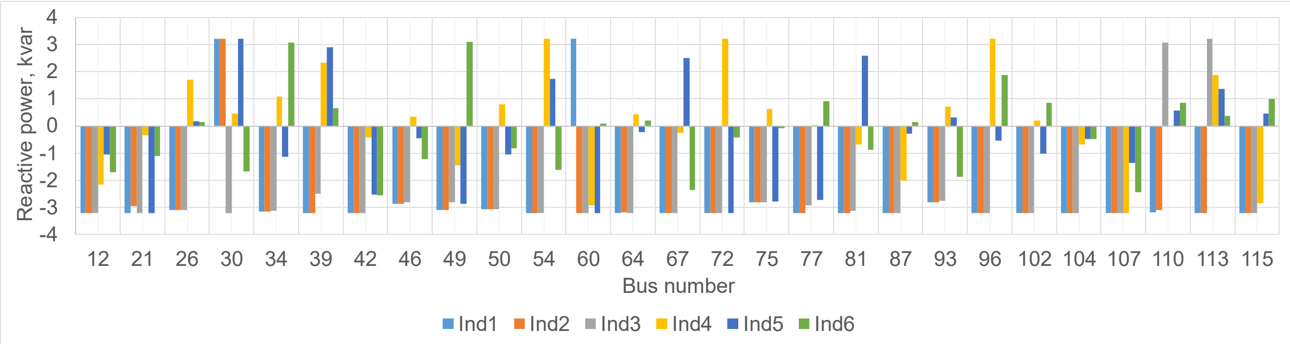

Fig. 11. The value of the optimal reactive power of sources for the following indicators using the WHO method

The presented solutions offer practical tools for managing low-voltage networks with a large share of distributed sources, which is particularly important in the context of the growing number of prosumer installations. With its help, it is possible to determine the optimal values of important network parameters in an accurate and mathematically justified way. The methodology for determining the values of individual quantities, which is easy to implement and present, allows to avoid discussions about the transparency and clarity of this process.

Among the compared power quality indicators in terms of both voltage and power losses, the best was indicator 5, i.e. the weighting function of the voltage factor and the power loss factor described by formula 5. Using it in combination with optimisation methods can bring benefits not only to companies managing distribution networks, but also have a positive impact on the operating conditions of prosumer installations. It allows for the selection of settings of individual elements in such a way that both parties can derive the greatest benefits while minimising regulation costs.

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LITERATURE

[1] Mroczek, B., Pijarski, P., Machine Learning in Operating of Low Voltage Future Grid. *Energies* 2022, *15*, 5388.
[2] Krzemiński, Z., Regulacja napięcia w sieci nN z rozproszonymi źródłami energii. *Przegląd Elektrotechniczny* 2020, *1*, 37–40.
[3] Pawlicki, B., Regulacja poziomu napięcia w zadaniu kształtowania zapotrzebowania na moc i energię elektryczną odbiorców końcowych w inteligentnych sieciach elektroenergetycznych. Rozprawa doktorska, Warszawa 2015.
[4] Adewuyi, O. B., Shigenobu, R., Ooya, K., Senjyu, T. et al., Static voltage stability improvement with battery energy storage considering optimal control of active and reactive power injection. *Electric Power Systems Research* 2019, *172*, 303–312.
[5] Homaee, O., Zakariazadeh, A., Jadid, S., Real-time voltage control algorithm with switched capacitors in smart distribution system in presence of renewable generations. *International Journal of Electrical Power & Energy Systems* 2014, *54*, 187–197.
[6] Mroczek, B., Pijarski, P., DSO Strategies Proposal for the LV Grid of the Future. *Energies* 2021, *14*, 6327.
[7] Rafał, K., Bielicki, S., Skoczkowski, T., Dynamiczna regulacja napięcia w sieci rozdzielczej z wykorzystaniem falowników generacji rozproszonej. *Przegląd Elektrotechniczny* 2016, *1*, 51–55.
[8] Tengku Hashim, T. J., Mohamed, A., Optimal coordinated voltage control in active distribution networks using backtracking search algorithm. *PloS one* 2017, *12*, e0177507.
[9] He, X., Wang, W., Jiang, J., Xu, L., An Improved Artificial Bee Colony Algorithm and Its Application to Multi-Objective Optimal Power Flow. *Energies* 2015, *8*, 2412–2437.
[10] Kołacz, T., Piekielniak, M., Skwarczyński, J., Wpływ odchyleń napięcia sieci energetycznej na sprawność silników indukcyjnych. *Sci. Tech., Innov* 2017, *4*, 91–97.
[11] Layth Al-Bahrani, Mircea Eremia, Optimal Power Flow (OPF) with different Objective Function based on modern heuristic optimization techniques, 2015.
[12] Kacejko, P., Adamek, S., Wydra, M., Optimal voltage control in distribution networks with dispersed generation, *2010 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT Europe)*. *2010 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT Europe)*, Gothenburg, Sweden, 11.10.2010–13.10.2010, IEEE, 2010, pp. 1–4.
[13] Kacejko, P., Pijarski, P., Optimal Voltage Control in MV Network with Distributed Generation. *Energies* 2021, *14*, 469.
[14] Pulluri, H., Rao, K. V. G., Sriram, C., Srikanth Goud, B. et al., Multiobjective optimal power flow solutions using nondominated sorting colliding bodies optimization. *Sci Rep* 2024, *14*, 26593.
[15] Sovann, A., Uthen, L., Thanatchai, K., Multi-Objective Real Power Loss and Voltage Deviation Minimization for Grid Connected Micro Power System Using Whale Optimization Algorithm. *International Energy Journal* 2018, 297–310.
[16] Shehab, M., Sihwail, R., Daoud, M., Al-Mimi, H. et al., Nature-Inspired Metaheuristic Algorithms: A Comprehensive Review. *IAJIT* 2024, *21*.
[17] Yang, X. S., Deb, S., Engineering optimisation by cuckoo search. *IJMMNO* 2010, *1*, 330.
[18] Mirjalili, S., Mirjalili, S. M., Lewis, A., Grey Wolf Optimizer. *Advances in Engineering Software* 2014, *69*, 46–61.
[19] Kennedy, J., Eberhart, R., Particle swarm optimization, *Proceedings of ICNN'95 – International Conference on Neural Networks*. *ICNN'95 – International Conference on Neural Networks*, Perth, WA, Australia, 27 Nov.-1 Dec. 1995, IEEE, 1995, pp. 1942–1948.
[20] Mirjalili, S., Moth-flame optimization algorithm: A novel nature-inspired heuristic paradigm. *Knowledge-Based Systems* 2015, *89*, 228–249.
[21] Mirjalili, S., Lewis, A., The Whale Optimization Algorithm. *Advances in Engineering Software* 2016, *95*, 51–67.
[22] Mohammed, H., Rashid, T., FOX: a FOX-inspired optimization algorithm. *Appl Intell* 2023, *53*, 1030–1050.
[23] Naruei, I., Keynia, F., Wild horse optimizer: a new meta-heuristic algorithm for solving engineering optimization problems. *Engineering with Computers* 2022, *38*, 3025–3056.
[24] El-kenawy, E.-S. M., Khodadadi, N., Mirjalili, S., Abdelhamid, A. A. et al., Greylag Goose Optimization: Nature-inspired optimization algorithm. *Expert Systems with Applications* 2024, *238*, 122147.
[25] Han, M., Du, Z., Yuen, K. F., Zhu, H. et al., Walrus optimizer: A novel nature-inspired metaheuristic algorithm. *Expert Systems with Applications* 2024, *239*, 122413.
[26] Al-Betar, M. A., Awadallah, M. A., Braik, M. S., Makhadmeh, S. et al., Elk herd optimizer: a novel nature-inspired metaheuristic algorithm. *Artif Intell Rev* 2024, *57*, 1–60.