**Sylwester FILIPIAK**

Politechnika Świętokrzyska

doi:10.15199/48.2024.09.03

# Application of a hybrid multi-criteria evolutionary-fireworks algorithm for the optimization of power systems operation

***Streszczenie.*** *Artykuł przedstawia koncepcję i analizy dla hybrydowego algorytmu ewolucyjno-fajerwerkowego zastosowanego do wielokryterialnej optymalizacji pracy systemów elektroenergetycznych. W analizach uwzględniono przyjęto kryteria optymalizacyjne dotyczące minimalizacji strat technicznych w analizowanych strukturach elektroenergetycznych, minimalizacji odchyleń napięcia, minimalizacji przeciążeń urządzeń sieciowych oraz optymalizacji rozpływów mocy w systemach. Zaprezentowane w artykule rezultaty przedstawiają możliwości zaproponowanego hybrydowego algorytmu zilustrowane i opisane na przykładzie wybranych zadań optymalizacyjnych. (**Zastosowanie hybrydowego wielokryterialnego algorytmu ewolucyjno-fajerwerkowego do optymalizacji pracy systemów energetycznych).***

***Abstract.*** *This paper presents the concept and analyses for a hybrid evolutionary-fireworks algorithm applied to multi-criteria optimisation of power system operation. The analyses consider optimization criteria related to minimizing technical losses in the analysed power system structures, voltage deviation minimization, reduction of network equipment overloads, and optimal power flow in the systems. The results presented in this paper demonstrate the capabilities of the proposed hybrid algorithm, illustrated and described through selected optimization tasks.*

**Słowa kluczowe**: sieci elektroenergetyczne, optymalizacja, metody ewolucyjne, algorytm fajerwerkowy
**Keywords**: power grids, optimization, evolutionary methods, fireworks algorithm

## Introduction

This paper presents the application of a hybrid multi-criteria algorithm that combines evolutionary methods with the concept of a fireworks algorithm. The article is a continuation and extension of the analyzes presented in the author's previous article, which contains the results of calculations using a hybrid evolutionary-fireworks algorithm for the approach integrating criteria.

The effectiveness of the computational approach used was analysed by comparing the results obtained with selected heuristic algorithms for optimizing power flow problems [12, 14, 15] in selected power system structures (contained in the Matpower package files). The analyses were carried out using Matlab and the Matpower package [2, 5, 9]. The evolutionary algorithm performs calculations of so-called simulated evolution, while the fireworks algorithm belongs to the group of swarm algorithms and utilizes descriptions of changes in the positions (locations in space) of sparks [5, 8, 10]. The group of evolutionary algorithms for the optimization in the Pareto meaning are designated as MOEA (Multi Object Evolutionary Algorithm) [1, 3, 4]. NSGA (Non-Dominated Sorting Genetic Algorithm) and improved versions NSGA II and NSGA III is popular method which differs from the basic genetic algorithm in the selection method. In the first step of NSGA, all non-dominated specimen are identified in the population and are given the same high value [6, 16]. Subsequently, in order to maintain the diversity, the pre-determined artificial values of adaptation of non-dominated specimen are subjected to the division function. In another step, new non-dominated solutions are identified in the remaining population [7, 11].

The paper outlines concepts and analyses for the hybrid multi-criteria evolutionary-fireworks algorithm used to determine Pareto-optimal solutions for the problem under analysis, the Pareto front, and solutions in the vicinity of the Pareto front. An original contribution of the paper is the concept of an evolutionary-fireworks algorithm applied to power flow optimization. Furthermore, the latter part of the paper extends the proposed hybrid algorithm concept to multi-criteria optimization of power system operation. In the multi-criteria optimization calculations, additional criteria were considered, including minimizing technical losses in the network, minimizing voltage deviations at network nodes, and minimizing network equipment overloads. This combination of algorithms has also been used in previous work [13], where evolutionary optimization of material flow in the injection moulding process for automotive components was presented. The effectiveness of the integrated approach of the fireworks and evolutionary algorithms for optimizing material flow in production processes was also analysed [13]. The focus was on the author's proposal for a hybrid approach. This paper proposes a new alternative concept for combining these algorithms, primarily involving the incorporation of recombination operators based on simulating secondary sparks, performed according to modified fireworks algorithm procedures. The hybrid algorithm's application for the optimization of power systems operation is also presented.

## Calculation methodology used

In the paper results of multi-criteria optimization analyses, considering a set of objective functions, were presented. The parameters of the evolutionary algorithm include population size and the intensity of recombination operators' usage. The appropriate choice of scaling and selection methods is also an important issue. In contrast, for the fireworks algorithm, the main parameters of the algorithm include the number of primary sparks, the amplitude of fireworks and the intensity of secondary sparks. The proposed hybrid algorithm is based on the assumption that the evolutionary algorithm is the main algorithm that processes the positions of points (corresponding to the location of the so-called primary sparks). On the other hand, the modified fireworks algorithm (incorporated into the crossover operator procedures) performs calculations for points generated around the primary spark, which corresponds to the generation of new variants of solutions (locations of secondary sparks) located near the primary point. In addition, a repository was included in the calculation, in which above-average solutions from both primary and secondary sparks are stored. The recombination operators of the evolutionary algorithm used transfer partial solutions (concerning the locations of primary sparks, the amplitude of fireworks, and the intensity of secondary sparks) between the configured new solutions.

The proposed hybrid approach makes it possible to increase the search intensity of the solution space for a single iteration, achieved at the cost of increased computational effort, but ultimately resulting in improved algorithm efficiency. Variant solutions include encoded locations of primary sparks, the amplitude of explosions, and the intensity of secondary sparks. This information was encoded in real-number vectors. The locations of primary spark and secondary sparks corresponded to various solution values for the analysed task. In the solution coding method used, the decision variables, once decoded, determined the levels of generated power at each source when the balancing node was taken into account. The coding method used also takes into account the limited ranges of values of the individual decision variables.

Operators that create new solution variants used in evolutionary algorithms have their limitations. The use of the proposed hybrid approach allows for the creation of more diverse solution variants by incorporating the fireworks algorithm procedures into the process of creating new solutions. In the applied hybrid approach, this algorithm involves processing a small sub-populations of solutions (created by a modified crossover operator). The developed crossover operator concept is based on the following steps:

- creation of solution variants (with a sub-population size generated from the range 3÷8) using the concept of secondary sparks,
- evaluation of sub-populations of solutions and inclusion of the best variants into the main population.

The applied recombination operators modify and create new solution variants that primarily describe the locations of primary and secondary sparks, as well as the values of secondary spark amplitudes. Determining the locations of fireworks involved calculating the values of decision variables and objective function values.

An extension of the proposed hybrid approach (the evolutionary-fireworks algorithm) for multi-criteria optimization was developed and analysed. This version of the algorithm is also based on the assumption that the evolutionary algorithm processes the main population of solutions, and the modified firework algorithm is activated when creating new solutions through recombination (crossover and mutation) operators. The proposed modifications to the NSGA II algorithm are indicated on the block diagram Fig.1 and Fig 2.

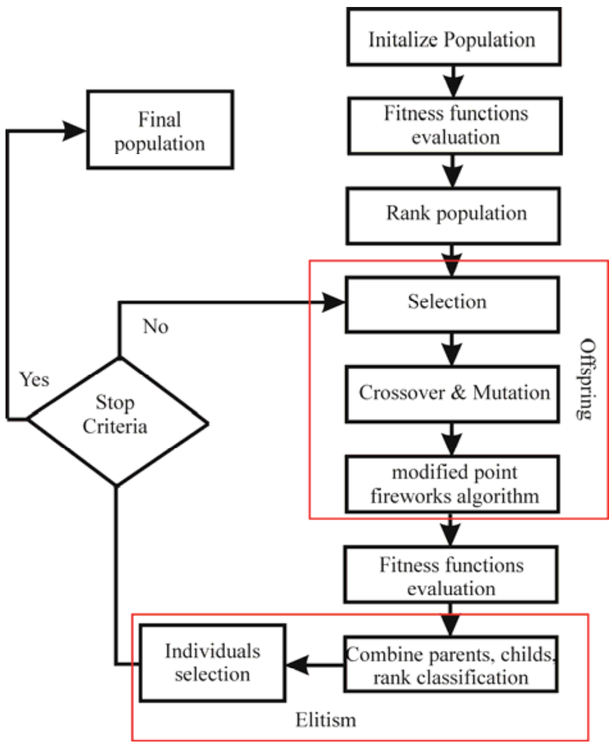


Fig 1. Block diagram of the modified NSGA II algorithm

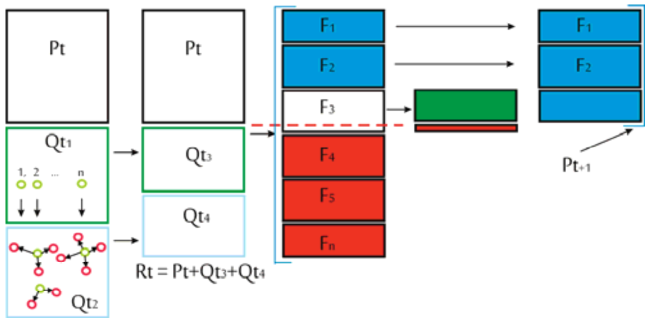


Fig 2. Iteration of the modified NSGA II algorithm (using the modfied fireworks algorithm)

where: $P_t$ – initial population; $Q_{t1}$ – the offspring made in the crossing and mutation process done on $P_t$; $Q_{t2}$ - based on $Q_{t1}$ made in modfied fireworks algorithm, $Q_{t3}$ - best solutions from $Q_{t1}$ (dominance criterion), $Q_{t4}$ - best solutions from $Q_{t2}$, $R_t$ – a population consists of $P_t$, $Q_{t3}$ and $Q_{t4}$; $F_1$ ÷ $F_n$ – Pareto sets created by sorting and ranking the members of population $R_1$, where $F_1$ contains the best population's members, $F_2$ to $F_n$.

Once a new solution variant has been created by the recombination operators, a sub-population of solutions corresponding to the secondary sparks used by the fireworks algorithm is created. These solutions are subject to evaluation (the degree of dominance is determined) and then some of these solutions (Pareto-optimal solutions) are included in the main population. During the evaluation, the degree of dominance of individual variants relative to other solution variants is determined. It is also possible to find solutions (slightly dominated) located close to the Pareto front. It is possible to apply the described hybrid approach in combination with the NSGA II algorithm (available in the "gamultiobj" function of the Matlab program) or the NSGA III algorithm.

The application of the described approach aims to determine the Pareto front for the analysed problems, improve the efficiency of recognizing the entire Pareto front, and achieve an even distribution of points on the Pareto front. New solutions generated by the modified point fireworks algorithm can replace the dominated (closest located) solutions in the created new population.

The proposed modification can also be used, for example, in the NSGA III algorithm. The hybrid approach provides additional possibilities for creating diverse solution variants compared to the classical versions of recombination operators. Modifications in the NSGA II algorithm involved making changes to the procedures of operators ("crossover" and "mutation") offered by the "gamultiobj" function. Below are the formulas for the criteria functions for the optimization criteria listed above.

$f_1(x)$ – the criterion function for the criterion under consideration can be represented as the summation of cost functions for individual generation nodes:

$$f_1(x) = \min_{Q,Vm,P_g,Q_g} \sum_{i=1}^{n} f_P^i(p_g^i) + f_Q^i(q_g^i) \quad (1)$$

where: $P_g$, $Q_g$ – vectors of values of generated active and reactive power, $Q$ – vector of values of voltage shift angles, $V_m$ – vector of values of nodal voltages,

$f_2(x)$ – determines the minimization of power losses in the analyzed MV grid:

(2) $$f_2(x) = \min\left(\sum_{i=1}^{n} \frac{P_i^2 + Q_i^2}{U^2} \cdot R_i(x) \cdot 10^3\right)$$

whereas: $R_i$ – resistance of the *i-th* section of the line after the upgrade,

$f_3(x)$ – the criterion function relates to the minimization of voltage deviations at the nodes of the analyzed field MV grid,

(3) $$f_3(x) = \min w_u = \min\left(100 \cdot \sqrt{\frac{1}{n} \cdot \sum_{i=1}^{n} \left(\frac{U_i - U_o}{U_n}\right)^2}\right)$$

whereas: $U_i$ – voltage at the *i-th* node, $U_o$ – expected voltage, $U_n$ – rated voltage, $n$ – number of nodes,

The paper also contains a description of results regarding the application of the described concept of a hybrid combination of selected versions of evolutionary and fireworks algorithms for multi-criteria optimization. The described hybrid approach can be implemented in the NSGA II algorithm through modifications of selected procedures of the NSGA II algorithm (available in the "gamultiobj" function). The modification involved: generating new points (solution variants) around the points generated by the main algorithm. Modification involved adding and modifying an external repository to store points on the Pareto front (or in its immediate vicinity according to the degree of dominance).

**Results of computational analyses**

Network structures stored as Matpower package files were analysed ("case 57", and "case 118"). Structure 57 is presented in [2], and Figure 3 shows a power nets with 118 nodes. In the initial stage of the analyses, calculations were performed for the objective function, where the criterion was the optimisation of power flows. In this part of the analysis, the results of calculations were compared using three algorithms:

- multi-criteria evolutionary algorithm (NSGA II),
- multi-criteria hybrid algorithm evolutionary-fireworks,
- multi-criteria particle swarm optimization (MOPSO).

The results presented in the paper were obtained using randomly generated initial populations of solutions, which were then processed by the (pre-selected) heuristic algorithms. Calculations using the basic evolutionary algorithm were performed with the following parameters: a population size ranging from 300 to 500 elements, a crossover operator probability of 0.8, and a mutation operator probability of 0.07. Calculations using the hybrid evolutionary algorithm were performed with the same parameters (as with the basic algorithm). The results obtained in the hybrid approach represent an improvement in algorithm efficiency, primarily due to the fact that the hybrid algorithm creates additional solutions, and the crossover operators have a broader range of capabilities for generating diverse solution structures compared to classical recombination operators.

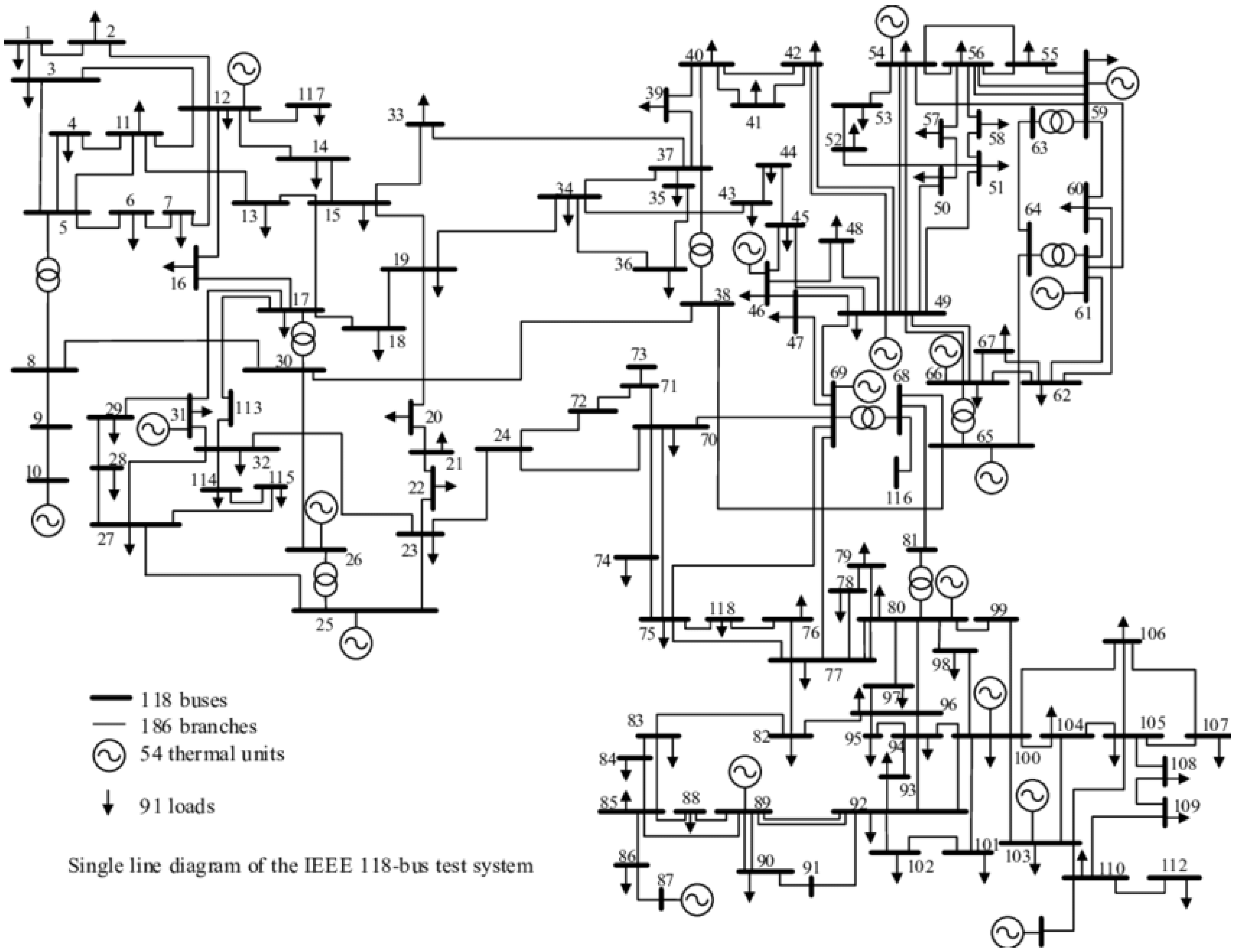


Fig. 3. Diagram of the IEEE 118-bus test system

The analyses were carried out for two power system structures stored in Matpower package files, namely: “case57” and “case118. The results obtained through this method were compared with the results obtained using the three algorithms. In particular, such a comparison is presented in Figures 4÷15, where these portions of the calculation process are shown in detail, illustrating the comparison of algorithm results.

In the graphs, it can be observed that the hybrid algorithm evolutionary-fireworks is the faster in finding the better solutions. In the analysed cases, the hybrid algorithm exhibits better efficiency compared to the basic evolutionary algorithm. For the structure containing 57 nodes, the minimum value of the objective function (energy production costs) is 41737 $/hr.

Figures 4÷12 show the course of optimization calculations using selected algorithms for two criteria minimizing energy production costs, minimizing technical losses in the network (taking into account active and reactive power losses). The following algorithm parameters were used for calculations: the number of population elements from 200 to 300, the number of iterations from 50÷250 or 350. For the NSGA II evolutionary algorithm, the intensity of the crossover operator was assumed to be 0.8, and the intensity of the mutation operator was 0.07.

For the hybrid evolutionary-fireworks algorithm, the intensity of secondary sparks was assumed to be from 3÷6, and the amplitude of secondary flares was from 0.03 to 0.05. Numerous computational processes were carried out using the pre-selected algorithms for optimizing the operation of various power system structures.

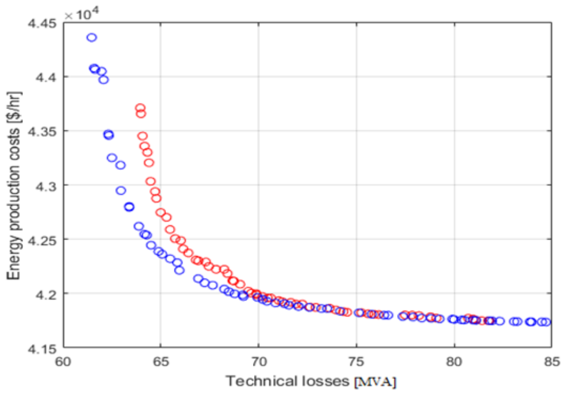


Fig. 4. Comparison of curves illustrating the course of calculations with selected algorithms for 50 iterations (NSGA II - red points, hybrid evolutionary-fireworks algorithm - blue points) for “case 57”

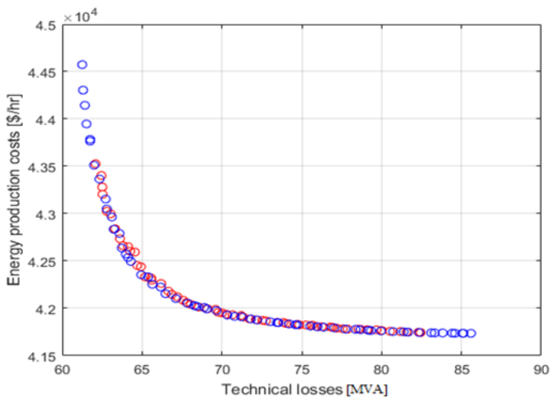


Fig. 5. Comparison of curves illustrating the course of calculations with selected algorithms for 150 iterations (NSGA II - red points, hybrid evolutionary-fireworks algorithm - blue points) for “case 57”

In Figures 4 - 12, a comparative search process for solutions using two algorithms is presented. The following notations were introduced in the comparison graphs: NSGA II - red points, and the modified NSGA II algorithm with application algorithm evolutionary-fireworks - blue points.

Table 1 provides a comparison of the objective function values for selected solution variants located in the middle of the discovered Pareto front. Calculations of indicators were also carried out to evaluate the position of the obtained Pareto fronts in relation to the assumed real Pareto front (or the nearest to the real one). Measures regarding the even distribution of points on the Pareto front can also be introduced for the evaluation of the created solutions.

Table 1. Values the objective function for selected solution variants located in the Pareto front ) for “case 57”

| No. | $f_1(x)$ - Energy production costs [$/hr] | $f_2(x)$ - Technical losses [MVA] |
|---|---|---|
| 1 | 41735,7 | 85,56 |
| 2 | 44722,9 | 61,15 |
| 3 | 41759,9 | 80,01 |
| 4 | 42403,3 | 64,93 |
| 5 | 44830,7 | 61,14 |

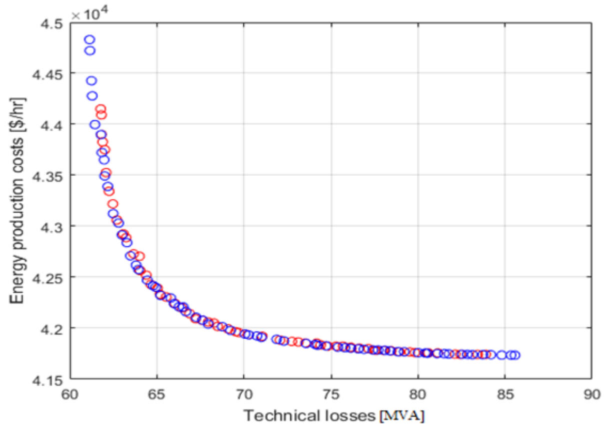


Fig. 6. Comparison of curves illustrating the course of calculations with selected algorithms for 250 iterations (NSGA II - red points, hybrid evolutionary-fireworks algorithm - blue points) for “case 57”

Indicators the distance between Pareto fronts obtained by selected algorithms were counted (algorithm NSGA II, hybrid evolutionary-fireworks algorithm) for power net “case 57". *Generational Distance (GD)* determines how far (on average) the found front is from the actual front [16]:

$$GD = \frac{1}{N_{known}} \cdot \sqrt{\sum_{i=1}^{N_{known}} d_i^2} \tag{4}$$

$$d_i = min_j \sum_{k=1}^{m} \left| f_k^i(x) - f_k^j(x) \right| \tag{5}$$

*Nknown* is the size of the found front, and $d_i$ determines the distance of each solution from the found solution front from the nearest solution from the actual solution front [16]. The lower the value of this metric, the closer the found front is to the real front. Obtained value of indicator for Pareto fronts for fig. 6: *GD* = 1.8961. Figure 7 shows a comparison of the results for the basic version of the NSGA II algorithm (for the number of iterations 350) and for the hybrid algorithm (for the number of iterations 250). A larger number of iterations of the basic NSGA algorithm gives a very similar effect to the result obtained with the hybrid algorithm with a smaller number of iterations.

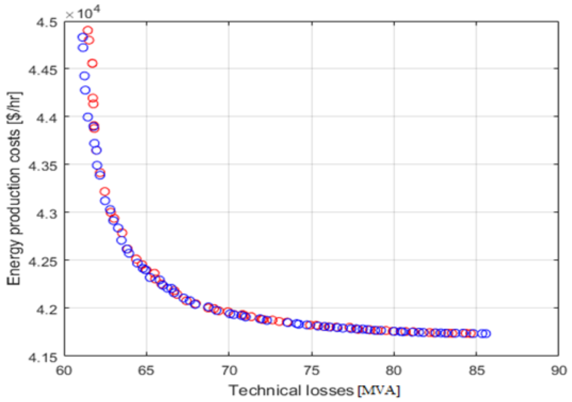


Fig. 7. Comparison of curves illustrating the course of calculations with selected algorithms for 350 iterations (NSGA II - red points, hybrid evolutionary-fireworks algorithm - blue points) for “case 57”

Figures 8 and 9 show the Pareto fronts obtained by the classical NSGA II algorithm and its modified version (hybrid evolutionary-fireworks algorithm) for optimization according to the adopted criteria for a 118-node structure. These figures show the differences in the results obtained by the classic NSGA II algorithm and its modified version using the evolution-fireworks algorithm.

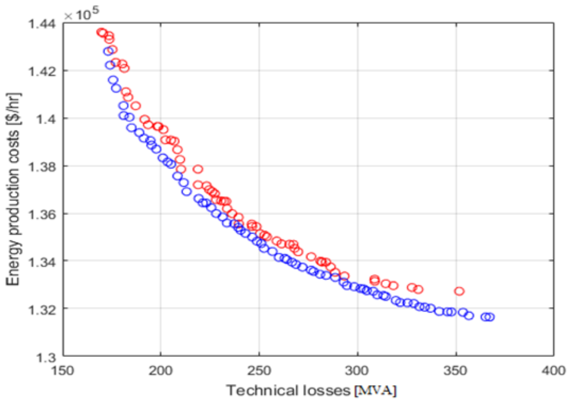


Fig. 8. Comparison of curves illustrating the course of calculations with selected algorithms for 50 iterations (NSGA II - red points, hybrid evolutionary-fireworks algorithm - blue points) for “case 118”

By comparing the obtained results, it can be observed that the hybrid multi-criteria evolutionary algorithm achieves better results than the basic evolutionary algorithm. Changes in the diversity of the population during the computational processes performed by the evolutionary algorithms (basic and hybrid) were also analysed. Changes in the diversity of the population during the computational processes performed by the evolutionary algorithms (basic and hybrid) were also analysed.

In particular, the histograms of solution evaluations at various stages of the optimization process were examined. After analysing the histograms of population evaluations, it was observed that the hybrid algorithm maintains greater population diversity compared to the basic evolutionary algorithm. This manifested itself in a more diverse population and better values of indicators determining the differences between the best elements of the population and the others. The proposed hybrid fireworks-evolutionary algorithm requires a greater number of single computations of the objective function per iteration, as it involves the evaluation of a sub-population of solution variants created by the modified firework algorithm.

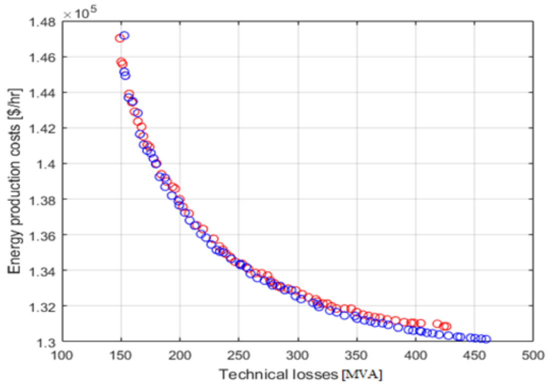


Fig. 9. Comparison of curves illustrating the course of calculations with selected algorithms for 300 iterations (NSGA II - red points, hybrid evolutionary-fireworks algorithm - blue points) for “case 118”

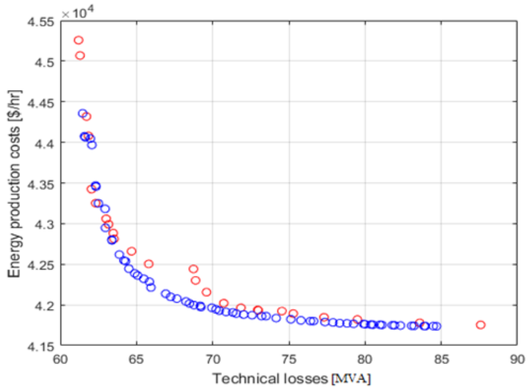


Fig. 10. Comparison of curves illustrating the course of calculations with selected algorithms for 50 iterations (MOPSO - red points, hybrid evolutionary-fireworks algorithm - blue points) for “case 57”

Analyses were also conducted for the application of the hybrid approach proposed in the paper using the MOPSO algorithm. In such a case, an improvement in results compared to the MOPSO algorithm was also obtained, as presented in Figures 10, 11 and 12.

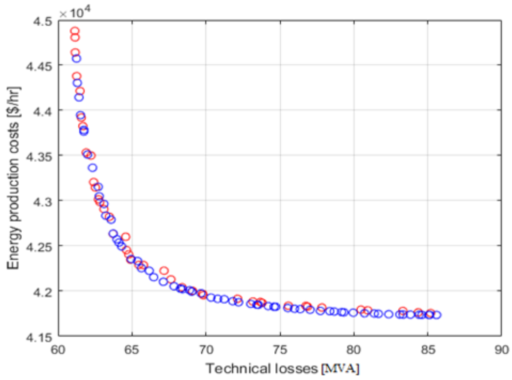


Fig. 11. Comparison of curves illustrating the course of calculations with selected algorithms for 150 iterations (MOPSO - red points, hybrid evolutionary-fireworks algorithm - blue points) for “case 57”

Analysing the results, it can be concluded that the analyses pertained to solving the problems analysed in the paper using the following algorithms: the NSGA II algorithm and its hybrid version, as well as the MSPO algorithm. Indicators the distance between Pareto fronts obtained by selected algorithms were counted (algorithm MOPSO, hybrid evolutionary-fireworks algorithm) for power net “case

57". Obtained value of indicator for Pareto fronts for fig. 12: *Generational Distance (GD)* = 2.1725.

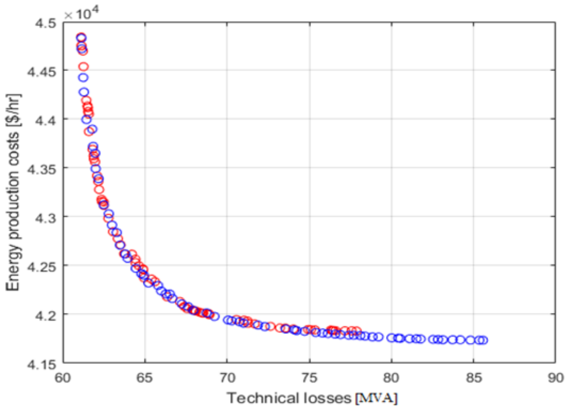


Fig. 12. Comparison of curves illustrating the course of calculations with selected algorithms for 250 iterations (MOPSO - red points, hybrid evolutionary-fireworks algorithm - blue points) for "case 57"

Figures 13÷14 show the course of optimization calculations for three criteria for the "case 57" network structure. The values of objective functions and decision variables for selected solution variants from the set of Pareto-optimal solutions are presented in Table 2.

The description of the algorithm parameters, such as the number of iterations and population size, is included in the description of the charts. The results presented in the chart (fig. 13) were obtained with a population size of 200 elements.

Table 2. Values the objective function for selected solution variants located in the Pareto front ) for power net "case 118"

| No. | $f_1(x)$ - Energy production costs [$/hr] | $f_2(x)$ - Technical losses [MVA] | $f_3(x)$ - Voltage deviations [j.w] |
|---|---|---|---|
| 1 | 41735,57 | 85,73 | 0,0649 |
| 2 | 44540,53 | 61,19 | 0,0638 |
| 3 | 46933,92 | 77,77 | 0,0634 |
| 4 | 43555,10 | 65,76 | 0,0635 |
| 5 | 44878,42 | 68,31 | 0,0634 |

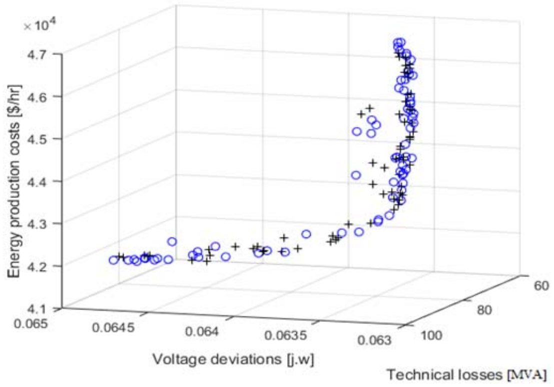


Fig. 13. Comparison of curves illustrating the course of calculations with selected algorithms for 50 iterations (NSGA II – black points, hybrid evolutionary-fireworks algorithm - blue points) for "case 57"

The results presented in the chart (fig. 14) were obtained with a population size of 300 elements for basic evolutionary algorithm (NSGA II) and the number of iterations equal to 500, and for population size of 200 elements for hybrid evolutionary-fireworks algorithm for the number of iterations equal to 200.

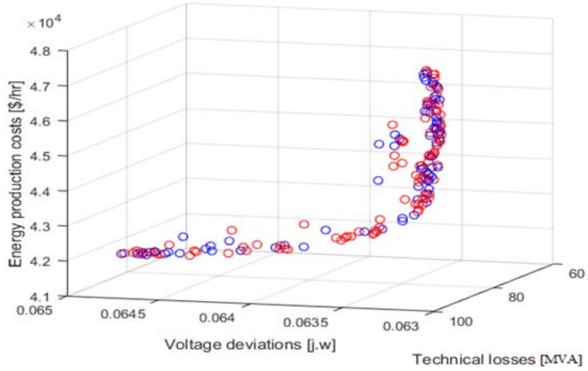


Fig. 14. Comparison of curves illustrating the course of calculations with selected algorithms for 200 iterations (NSGA II - red points, hybrid evolutionary-fireworks algorithm - blue points) for "case 57"

Figure 15 shows the course of optimization calculations for three optimization criteria (minimizing technical losses in the network, minimizing voltage deviations at network nodes, and minimizing energy production costs) for the "case 118" net structure.

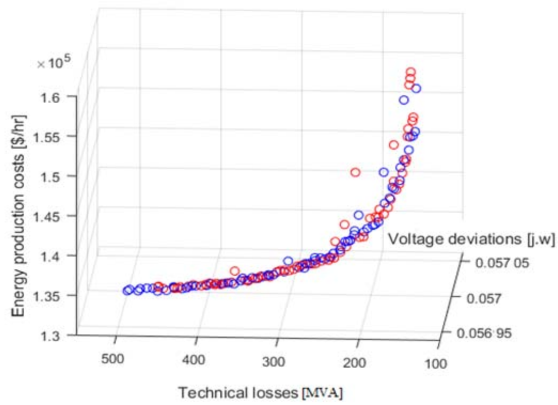


Fig. 15. Comparison of curves illustrating the course of calculations with selected algorithms for 300 iterations (NSGA II - red black, hybrid evolutionary-fireworks algorithm - blue points) for "case 118"

Based on the analyses performed, it can be observed that the proposed modifications and extensions of the NSGA II evolutionary algorithm (available in the "gamultiobj" function of Matlab) allow for an improvement in the efficiency of this algorithm. This improvement is in the graphs illustrating the obtained sets of Pareto-optimal solutions. The results of the conducted analyses are also presented in tables containing the values of the objective functions for selected solution variants of the problem analysed in the paper.

**Conclusions**

The paper presents the results of analyses on the application of modified versions of evolutionary algorithms in multi-criteria optimisation, and the capabilities of the proposed hybrid approach (combined evolutionary and fireworks algorithms) for finding a set of Pareto-optimal solutions. This paper presents analyses related to multi-criteria optimization using selected evolutionary algorithms and their proposed modifications.

The results obtained indicate a positive impact of the proposed modifications (in the form of a hybrid approach) of evolutionary algorithm on their effectiveness. In the paper, the results of multi-criteria optimization analyses, considering a set of objective functions (minimizing energy production costs, minimizing technical losses in the network, minimizing voltage deviations at network nodes), were presented. Analyses were carried out using three selected heuristic algorithms: the particle swarm algorithm and the basic and hybrid versions of the evolutionary algorithm.

The analyses carried out led to the conclusion that the proposed hybrid algorithm offers additional capabilities compared to the basic version of the evolutionary algorithm. The proposed hybrid algorithm can be extended to include further criteria and determine Pareto-optimal solutions. The analysis showed the possibility of applying the proposed hybrid algorithm in its basic version, but it can also be adapted for multi-criteria computations to determine a set of Pareto-optimal solutions and the Pareto front.

*Autor: dr hab. inż. Sylwester Filipiak prof. PŚk, Politechnika Świętokrzyska w Kielcach, Katedra Energetyki, Maszyn Elektrycznych i Energoelektroniki, E-mail: filipiak@tu.kielce.pl*

## References

[1] Ciro G., Dugardin F., Yalaoui F., Kelly R.: A NSGA-II and NSGA-III comparison for solving an open shop scheduling problem with resource constraints. IFAC, *International Federation of Automatic Control*, 2016 s. 1272–1277.

[2] Delbem A. C. B., Carvalho A. C. P. L. F., Bretas N. G.: Main chain representation for evolutionary algorithms applied to distribution system reconfiguration. *IEEE Trans. Power Systems*, vol. 20, no. 1, Feb. 2015, pp. 425-436.

[3] Daniel Gómez-Lorente, Isaac Triguero, Consolación Gil, Rabaza: Multi-objective evolutionary algorithms for the design of grid-connected solar tracking systems. *International Journal of Electrical Power & Energy Systems*. Volume 61, October 2014, pp. 371–379.

[4] Guohua Fang, Wei Guo, Xianfeng Huang, Xinyi Si, Fei Yang, Qian Luo, Ke Yan: A New Multi-objective Optimization Algorithm: MOAFSA and its Application. *Przegląd Elektrotechniczny*, R. 88 Nr 9b/2012, s. 172-176.

[5] Niknam T., Farsani E. A., Nayeripour M., Firouzi B. B.: Hybrid fuzzy adaptive particle swarm optimization and differential evolution algorithm for distribution feeder reconfiguration. *Electric Power Components and Systems*, vol. 39, Issue 2, 2011, pp. 158 – 175.

[6] Khushalani S., Solanki, J.M., Schulz, N.N. Optimized Restoration of Unbalanced Distribution Systems. *IEEE Transactions on Power Systems*, no. 22, Issue 2. 2007, p. 624-630.

[7] Helt P., Parol M., Piotrowski P.: Metody sztucznej inteligencji – przykłady zastosowań w elektroenergetyce. Oficyna Wydawnicza Politechniki Warszawskiej, 2012.

[8] Hong Y. Y., Ho S. Y.: Determination of network configuration considering multiobjective in distribution systems using genetic algorithms. *IEEE Trans. Power Systems*, 2005. – Vol. 20. – No. 2. – p. 1062–1069.

[9] Janik P.: Porsinger T., Leonowicz Z., Gono R.: Modelling and Optimization in Microgrids, Energies, 2017, p. 161-170,

[10] Kumar Y., Das, B., Sharma, J.: Multiobjective, Multiconstraint Service Restoration of Electric Power Distribution System With Priority Customers. *IEEE Transactions on Power Delivery*, no. 23, Issue 1, 2008, p. 261-270.

[11] Marzecki J., Drab M.: Obciążenia i rozpływy mocy w sieci terenowej średniego napięcia-wybrane problemy. Przegląd Elektrotechniczny, R.91, pp. 192-195, luty, Nr 2, 2015.

[12] Parol M., Baczyński D., Brożek J.: Optimisation of Urban MV Multi-Loop Electric Power Distribution Networks Structure by Means of Artificial Intelligence Methods, Control and Cybernetics, 2012, vol. 41 (2012), s.667-689.

[13] Paździor, P.: Optymalizacja ewolucyjna przepływu materiału w procesie formowania wtryskowego komponentów dla branży motoryzacyjnej. Rozprawa doktorska 2021, Wydawnictwo Politechniki Śląskiej.

[14] Pijarski P.: Optymalizacja heurystyczna w ocenie warunków pracy i planowaniu rozwoju systemu elektroenergetycznego. Monografia, Wydawnictwo Politechniki Lubelskiej, Lublin 2019.

[15] Pijarski P., Sidor K., Miller P.: Zastosowanie optymalizacji konfiguracji sieci do redukcji kosztów strat energii elektrycznej, *Przegląd Elektrotechniczny* R. 95 nr 10/2019, s. 110-113.

[16] Sharma D., Thulasiraman K., Jiang D.: A network science-based k-means++ clustering method for power systems network equivalence. Computational Social Networks volume 6, Article number: 4 (2019).