

NOVEL DE-BASED OPTIMIZATION TECHNIQUE
FOR THE RENEWABLE SOURCES' INTEGRATION

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Abstract

Ever since the thermal generation units, once a foundation of a large number of the power systems, were marked as one of the main emitters of greenhouse gases and, therefore, undesirable in the modern systems, the renewable energy sources are taking over their share in the generation mix. Although this process is going fast, it might still not be efficient enough to reach the climate goals, set with short deadlines. In accordance with that, every measure that enhances the integration of renewable sources into the grid and makes the application process for the new investors simple and straightforward is welcome. To aid that cause, this paper proposes the method for determining the optimal location of the new wind power plant in the predefined geographical area, taking into account both the characteristics of the power system in that region and the relevant climatic indicators. This technique was developed by utilizing the differential evolution mechanism, while introducing a novel space search formula that ensures the avoidance of the local optima. For the mapping of the solutions and switching between the discrete and continuous values, the georeferencing principle was implemented. This method was illustrated on the part of the Serbian real-life system.

Key words: centroid location, climatic indicators, differential evolution, georeferencing, renewables

Introduction. The integration of renewable energy sources is a subject that has thrived the most out of all topics related to power systems in the past several

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decades. One of the main points of interest for the experts in this area is defining the optimal location in which the energy source should be built. This claim is witnessed by a large number of published papers dedicated to the exact same topic [1,2].

This paper presents a method for finding the location in which the generation capacity should be built in order to ensure that the maximal amount of energy may flow from it into the system. For the example of the real-life system, the part of the Serbian transmission grid was chosen. It was taken that the wind power plant is getting connected to the grid. Since the optimization techniques showed good results in dealing with many engineering problems [3-5], it was decided to use one of them in this paper as well. That technique is based on the modified differential evolution, praised for accuracy, efficiency and fast convergence, especially when compared to some of the other optimization methods [6,7].

Differential evolution has a long history in the optimization of the power systems' operation [8-10]. The papers that would be of particular interest here are the papers in which the differential evolution was used for obtaining the optimal location of the distributed energy sources in the grid [11,12].

The presented technique combines the measurements of the relevant climatic indicators with the optimal power flow calculations and system security assessments in order to provide the coordinates of the optimal solution for the specified problem. As the objective function, the maximal sum of powers by which the energy can be pumped into the system in the three extreme system working regimes was chosen. The year of 2030 was taken as the reference year. The vital novel step is the modification of the differential evolution's search mechanism. A methodology grounded on finding a centroid of a triangle is described. This improvement was included in order to aid escaping the local optima.

Nomenclature. This part gives an explanation of the used symbols and abbreviations:

- WP – Winter Peak;
- SP – Summer Peak;
- AM – Absolute Minimum;
- ACSR – aluminium conductor steel reinforced;
- GDP – gross domestic product;
- N – number of solutions per population;
- $\mathbf{s}$ – solution vector;
- i – index of a solution in a population;

- g – index of an iteration;
- x – first coordinate of a point;
- y – second coordinate of a point;
- k – index of an element of the solution;
- r – index of a solution used in the mutation;
- F – mutation factor;
- $rand$ – random real number $[0,1]$;
- $randint$ – random integer $\{1,2\}$;
- $\mathbf{v}$ – donor vector;
- $\mathbf{u}$ – trial vector;
- v_{wind} – wind speed [m/s];
- P_{gen} – power of generation of the wind unit;
- P_{genWP} – power of generation of the wind unit in the Winter Peak regime;
- P_{genSP} – power of generation of the wind unit in the Summer Peak regime;
- P_{genAM} – power of generation of the wind unit in the Absolute Minimum regime;
- CP – crossover probability;
- G – total number of iterations in the optimization;
- K_i – fitness function value of the solution i .

Description of the system. The simplified diagram of the part of the Serbian 110 kV network used for demonstration of the developed technique is provided in Fig. 1.

This part of the system contains 32 nodes, connected by 43 lines. The voltage of all 110 kV buses needed to remain between 99 and 121 kV [13]. It was taken that all of the lines in this segment of the system were equipped with the ACSR type conductors, with the cross-section of 240/40 mm². These are common characteristics for the new 110 kV lines in the Serbian system.

The maximal load in this area in the previous period was 1784 MW. As this paper took 2030 as the reference year, it was necessary to estimate the load change until then. For that, the artificial neural network was used [14]. The network was

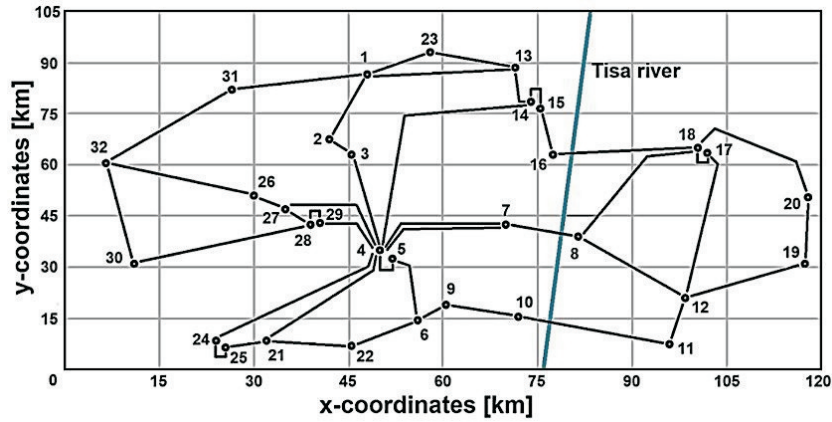


Fig. 1. Part of the Serbian transmission system

trained by using the load values obtained from the Ten-year network development plan of Serbian TSO [15]. The load is expected to grow by around 7% until 2030, giving this area a maximal load of about 1905 MW.

Working regimens. The three extreme working regimens that were used for the analyses were the WP regime (due to the yearly maximum of load, overloads may occur), SP regime (70% of the WP load, dire since the rating of the lines is lower than in the WP regime, increasing the possibility of overloads further) and AM regime (40% of the WP load, has the highest possibility of overvoltages). As the higher wind speeds mean more critical conditions for the wind farm integration, it was necessary to determine the highest wind speeds that could be expected in the area in the hours in which the regimes may happen. For that, the typical daily demand diagram was used [16]. As the maximal daily consumption commonly occurs between 18:00 and 21:00, these hours were used to determine the wind speeds in WP and SP regimes. The minimal daily load values happen between 02:00 and 05:00, so these hours were selected for AM regime. As the representative interval for the WP regime, the period between 01.12. and 31.01. was taken. As the relevant interval for the other two regimes, the period between 15.06. to 15.08. was chosen.

Then, the entire area was divided into three zones, corresponding to the wind potential each of them possesses [17]. In the area, zones 1, 2 and 3, respectively, had the wind potential of 0–100 W/m² (node 32), 100–200 W/m² (nodes 1–5, 7, 8, 13–16, 20, 21, 23–31) and 200–300 W/m² (the remaining nodes).

Afterwards, each zone was assigned with the maximal wind speed for every regime, as enclosed in Table 1. Here, the available measurements were used, with the missing data getting compensated by combining the fact that the wind profile remains the same regardless of the zone and the formula by which the wind power is directly proportional to the cubed value of the wind speed [18].

T a b l e 1

The wind speeds for the created zones

v_{wind} [m/s]	Zone 1	Zone 2	Zone 3
<i>WP regime</i>	10.22	14.74	17.48
<i>SP regime</i>	5.94	8.56	10.15
<i>AM regime</i>	5.57	8.03	9.52

For the conversion of the wind speeds to the corresponding wind farm power, the typical production diagram was utilized, with the cut-in, nominal and cut-out wind speeds given in [19].

Optimization technique. By setting the reference point into the bottom left angle of Fig. 1, each point in this area was assigned two coordinates, in line with the georeferencing principle. For the number of potential solutions in a population, $N = 10$ solutions was selected. This value was adopted to ensure the sufficient scatter of the candidate solutions. Each solution $\mathbf{s}$ in the iteration g could be written in the form given by (1).

$$(1) \quad \mathbf{s}_i^g = \{x_{\mathbf{s}_i}^g, y_{\mathbf{s}_i}^g\}, \quad i = 1, 2 \dots N.$$

After generating the initial population, the first iteration was commissioned. There, for every solution $\mathbf{s}$ (*target vector*) in the initial population, the competing solution (*trial vector*) was created. Its formation began by creating *donor vector*. For the solution i in the iteration g , the donor vector was spawned in the *mutation* process, by picking the three solutions' indices r , honouring the restriction (2).

$$(2) \quad r_1 \neq r_2 \neq r_3 \neq i.$$

In the conventional differential evolution, element k of the donor vector $\mathbf{v}$ is calculated by adding the difference of the elements k of the second and third solution, scaled by the mutation factor F , to the element k of the first solution (3).

$$(3) \quad \mathbf{v}_{i,k}^g = \mathbf{s}_{r_1,k}^g + F \times \left(\mathbf{s}_{r_2,k}^g - \mathbf{s}_{r_3,k}^g \right).$$

However, if the second and third solution are close to each other, the donor vector could be near the first selected solution, leaving the calculations prone to finding the local optima. The novel methodology uses the *centroid formula* for determining a donor vector (4), with the impact illustrated in Fig. 2.

$$(4) \quad \mathbf{v}_{i,k}^g = \mathbf{s}_{r_1,k}^g + \frac{2}{3} \times \left(\frac{\mathbf{s}_{r_2,k}^g + \mathbf{s}_{r_3,k}^g}{2} - \mathbf{s}_{r_1,k}^g \right).$$

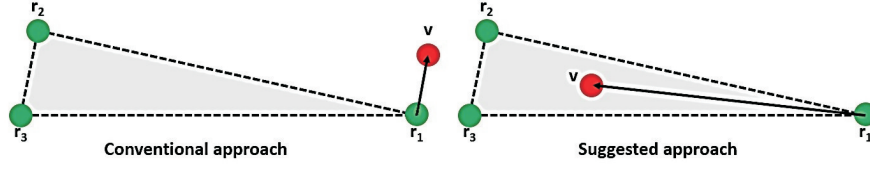


Fig. 2. Donor vector generation in both approaches

The trial vector $\mathbf{u}$ was generated in the *crossover* process. For every target vector $\mathbf{s}_i^g$, the random integer value $randint_i^g$ lower than 3 was generated. For each element of the target vector, the random real number $rand_{i,k}^g$ was generated in the range of 0 to 1. The trial vector was then assembled (5).

$$(5) \quad \mathbf{u}_{i,k}^g = \begin{cases} \mathbf{v}_{i,k}^g, & (rand_{i,k}^g \leq CP) \vee (k = randint_i^g) \\ \mathbf{s}_{i,k}^g, & (rand_{i,k}^g > CP) \wedge (k \neq randint_i^g) \end{cases}.$$

For the probability of the crossover, the value of 0.8 was presumed [6]. The point of adding the $randint_i^g$ in (5) was preventing the event in which the trial vector would be identical to the target vector.

After taking that the plant is built in the location suggested by the solution and that it is connected to the node that is closest to it (by the maximal cost reduction principle), the three-step procedure was performed to obtain the solution's fitness function:

- 1) The system was set to the WP regime. The available capacity of the wind plant was calculated by using Table 1, diagram from [19], and the assumption that the installed capacity of the plant is 300 MW. Then, the maximal allowed generation power was calculated. This was done by the AC optimal power flow procedure [20], with the minimal cost of the total production as a proof of reaching the best possible state of the system. The unit production cost of the wind plant was set as lower than the other generating capacities. This granted it the priority over other sources.
- 2) The $N - 1$ security assessment was performed by simulating the outage of every line in the system and repeating the calculation from step 1). The lowest generation value obtained in these cases (and in the base state from step 1)) was taken to represent the WP regime, as it was seen as the maximal tolerable power by which the production may occur.
- 3) The procedure from steps 1) and 2) was done for the remaining two regimes. The fitness function of the solution was calculated by calculating a total of the production values obtained for the selected three regimes.

This procedure can be abbreviated to (6).

$$(6) \quad K_i = \min(P_{genWP}) + \min(P_{genSP}) + \min(P_{genAM}).$$

The next step was the *tournament selection*. The values of the fitness functions of the target vector and the trial vector were then compared. The solution with the higher fitness function value was added to the next population. The other solution was deleted. This procedure was repeated in each iteration until the number of iterations G (in this paper, 10) was reached. The solution with the highest fitness function value in the final population was declared optimal.

Results. The solutions suggested by the novel technique and the conventional differential evolution can be seen in Table 2, from which it is obvious that the novel method had suggested the better solution than the commonly used differential evolution mechanism. This also confirms the statement made earlier in the paper that the introduced search method aids the optimization in avoiding the local minima. For the conventional method, the value of 0.9 was taken for the mutation factor [6].

T a b l e 2

The results obtained by both approaches

	x [km]	y [km]	Zone	The closest node	K_i [MW]
<i>Novel method</i>	52.16	10.63	3	6	672.14
<i>Conventional method</i>	49.16	16.65	3	22	521.33

Following this, the obtained solution was also verified by the brute-force check in which the three-step procedure was done for the entire enveloped area, with the resolution of 1 km. The results obtained during this process matched the suggestion of the novel methodology perfectly, proving the proposed value of the fitness function as the one corresponding to the best location choice. This check confirmed that the suggested solution is, in fact, the correct one and that the novel method not only managed to beat the conventional method, but also locate and provide the real optimal solution of the problem.

Conclusion. The idea behind this paper was the development of the novel optimization technique, based on differential evolution, with the goal of nominating the optimal location of the new wind farm. For that, the differential evolution was modified by using the new mutation mechanism, based on the triangle centroid formula. The noteworthy aspects are also using georeferencing for mapping possible solutions and inclusion of the measured climatic indicators, such as the wind speeds, into the equation. The results have fully proven the novel method's success in upgrading the existing technique significantly.

This paper can be seen as a basis for future papers dealing with similar topics, as the authors have plans to conduct examination of the method's behaviour in

case of additional complexities, such as the inclusion of different renewable sources, considering other regimes or dividing the area into more zones. Each of these could end up being a subject for a new research in the years to come, built upon the foundation that has been set in this paper.

REFERENCES

- [¹] KHAN M. Y., M. ALI, S. QAISAR, M. NAEEM, C. CHRYSOSTOMOU et al. (2020) Placement Optimization for Renewable Energy Sources: Ontology, Tools, and Wake Models, *IEEE Access*, **8**, 72781–72800.
- [²] KRAEMER C., K. GOLDBERMAN, C. BREUER, P. AWATER, A. MOSER (2013) Optimal positioning of renewable energy units. In: *Proc. 2013 IEEE Energytech*, Cleveland, Ohio, USA, 1–5.
- [³] GOKCE B., Y. B. KOCA, Y. ASLAN, C. O. GOKCE (2021) Particle Swarm Optimization-based Optimal PID Control of an Agricultural Mobile Robot, *C. R. Acad. Bulg. Sci.*, **74**(4), 568–575.
- [⁴] MURUGAN S., B. MARIAPPAN (2020) Self Learning Ant Colony Optimization in Multipath Routing Ad Hoc Network, *C. R. Acad. Bulg. Sci.*, **73**(10), 1425–1433.
- [⁵] BELLABAI R., J. ROBERT, R. RAJKUMAR (2019) Multi-objective Optimization Using Hybrid Algorithm and Its Application to Scheduling in Flow Shops, *C. R. Acad. Bulg. Sci.*, **72**(1), 107–114.
- [⁶] STORN R., K. PRICE (1997) Differential evolution – A simple and efficient heuristic for global optimization over continuous spaces, *J. Global Optim.*, **11**, 341–359.
- [⁷] HANG N. T. T., H. CHIKAMORI (2017) Comparison of efficiency between differential evolution and evolution strategy: application of the LST model to the Be River catchment in Vietnam, *Paddy Water Environ.*, **15**, 797–808.
- [⁸] MUTHAMIL SELVI C., K. GNANAMBAL (2011) Power system voltage stability analysis using modified differential evolution. In: *Proc. 2011 International Conference on Computer, Communication and Electrical Technology (ICCCET)*, Tamilnadu, India, 382–387.
- [⁹] SUM-IM T., W. ONGSAKUL (2012) A self-adaptive differential evolution algorithm for transmission network expansion planning with system losses consideration. In: *Proc. 2012 IEEE International Conference on Power and Energy (PECon)*, Kota Kinabalu, Malaysia, 151–156.
- [¹⁰] SOSIC D., P. STEFANOV (2019) Reconfiguration of distribution system with distributed generation using an adaptive loop approach, *Journal of Electrical Engineering*, **70**(5), 345–357.
- [¹¹] ESTABRAGH M. R., M. M. MOHAMMADIAN (2011) Optimal allocation of DG regarding to power system security via DE technique. In: *Proc. 2011 IEEE Jordan Conference on Applied Electrical Engineering and Computing Technologies (AEECT)*, Amman, Jordan, 26–31.
- [¹²] ALI MOHAMED A. A., S. M. ALI, A. M. HEMEIDA, A. A. IBRAHIM (2019) Optimal placement of distributed energy resources including different load models using different optimization techniques. In: *Proc. 2019 International Conference on Innovative Trends in Computer Engineering (ITCE)*, 389–395.

- [¹³] JSC Elektromreza Srbije (2020) Rules on operation of the transmission system, <http://ems.rs> (accessed in January 2021), (in Serbian).
- [¹⁴] ZARKOVIC M., D. SOSIC, G. DOBRIC (2014) Fuzzy based prediction of wind distributed generation impact on distribution network: Case study – Banat region, Serbia, *J. Renewable Sustainable Energy*, **6**(1), 1–12.
- [¹⁵] JSC Elektromreza Srbije (2019) Development plan of the transmission system of the Republic of Serbia for the period 2020–2029, <https://www.aers.rs> (accessed in January 2021), (in Serbian).
- [¹⁶] BAILES A. (2015) Electricity demand and the duck curve, <https://www.energyvanguard.com>, (accessed in January 2021).
- [¹⁷] KATIC V., B. DUMNIC, N. KATIC, D. MILICEVIC, S. GRABIC (2012) Potentials and market prospects of wind energy in the province of Vojvodina, *Therm. Sci.*, **16**(Suppl. 1), S141–S157.
- [¹⁸] ecoCAD Design Group, LLC (2011) Wind Pitch Experiments for the Blade Design and Performance Kit, <http://solidwize.com>, (accessed in January 2021).
- [¹⁹] MOHANPURKAR M. U., R. RAMAKUMAR (2010) Probability density functions for power output of Wind Electric Conversion Systems. In: *Proc. Power and Energy Society General Meeting*, Minneapolis, Minnesota, USA, 1–7.
- [²⁰] CAIN M. B., R. P. O’NEILL, A. CASTILLO (2012) History of optimal power flow and formulations, <https://www.ferc.gov>, (accessed in January 2021).

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