ELEKTROTEHNIŠKI VESTNIK 86(5): 253-258, 2019
ORIGINAL SCIENTIFIC PAPER

Multi-objective DG allocation in a radial power distribution network for power loss reduction, voltage profile improvement and investment deferral

Mirza Šarić[1], Jasna Hivziefendić[1], Tatjana Konjić[2]

[1]Affiliation: International Burch University, Bosnia and Herzegovina
[2] University of Tuzla, BiH

E-mail: mirza.saric@ibu.edu.ba

Abstract. The paper presents a method for the Distributed Generation (DG) allocation planning based on a multi-objective genetic algorithm for power loss reduction, voltage profile improvement and investment deferral. The problem is approached as a multi-objective, constrained optimization problem. The best trade-off among the candidate solutions from the Pareto front is obtained using fuzzy multi-criteria decision-making based on the Bellman-Zadeh method. The algorithm is applied to a realistic medium voltage power distribution system in order to demonstrate its practical relevance. Results demonstrate that both DG distribution and penetration level affect the objective functions, which tend to be optimized at a medium DG penetration and high distribution levels. It is demonstrated that the presented algorithm is applicable for a realistic power system and that it provides an insight into the impact of the DG integration on various network parameters. The paper is expected to improve the existing DG planning process and its results will be used in practical situations by planning engineers of the Utility and Regulatory bodies.

Keywords: Distributed power generation, decision-making, genetic algorithm, fuzzy systems, load flow, power generation planning

Večkriterijska optimizacija lokacije razpršenih virov v radialnem distribucijskem elektroenergetskem omrežju za zmanjšanje izgub in izboljšanje napetostnega profila

V prispevku je predstavljena večkriterijska optimizacija lokacije razpršenih virov v radialnem distribucijskem elektroenergetskem omrežju s ciljem zmanjšanja izgub, izboljšanja napetostnega profila in ekonomskim učinkom. Najboljše rešitve iz množice Pareto smo izbrali z metodo Bellman-Zadeh. Algoritem smo uporabili na resničnem srednjenapetostnem elektroenergetskem omrežju in prikazali njegovo uporabnost. Dobljeni rezultati potrjujejo, da porazdelitev in delež razpršene generacije vplivata na kriterijske funkcije. Pokazali smo, da lahko predlagano metodo uporabimo na resničnem elektroenergetskem omrežju in da nam omogoča analizo priključitve razpršenih virov v omrežje.

1 INTRODUCTION

Modern power systems are undergoing significant organizational, structural and technological changes driven by the processes of market liberalization and energy transition from the conventional energy sources to the renewable energy. In Europe, the comprehensive process of market liberalization was first initiated in the UK and was later adopted by all European Union members. Distributed generation (DG) offers a promising new approach for improvement of the power distribution system performance in terms of the voltage profile and reliability improvement, power loss reduction, equipment lifetime extension and investment deferral [1]. However, the existing literature and practical experience provide a considerable support to the claim that DG can cause significant challenges in the network. In some cases, DG can deteriorate the network quality parameters and create more costs than benefits. Poor allocation and intermittent nature of DG power output create locational and temporal mismatches of the supply and demand and cause a number of technological, economic and social challenges, which means that the DG allocation optimisation is a key factor for achieving the benefits of new DG units [2]. DG facilities will be beneficial only if they are optimally located and sized using a single or multi-objective function under certain operating constraints [3]. For these reasons, DG allocation continues to be an important area of engineering research.

Received 28 December 2018
Accepted 17 September 2019

The paper presents a method for DG allocation planning based on a multi-objective genetic algorithm and fuzzy multi-criteria decision-making. It contributes to the existing body of knowledge by proposing a soft computing method, applied to a real power distribution system in order to reduce the energy losses, improve voltage profile and prolong the lifetime of the power system components. Furthermore, the proposed model can be used as powerful insight into power system behaviour and as an analytical tool supporting various Regulatory bodies for various regulatory and tariffing purposes.

2 LITERATURE REVIEW

The DG allocation problem can be addressed as a single or a multi-objective optimisation problem. It is usually expressed as a constrained problem, since the basic system parameters must remain within the set limits. Single objective settings of the problem are simpler to implement and require less time to converge. Multi-objective algorithms are more complex but are capable to create better models, which more realistically represent the system. They offer the possibility to select the best option based on the trade-off between conflicting objectives. The most frequently considered planning objective includes power loss minimisation, voltage and reliability improvement, DG power output maximisation and cost minimisation [4]. Technical advancement and regulatory changes encourage the proposition of additional objectives such as the total emission reduction [1] and operational cost minimisation [5].

The DG allocation constraints can be defined as equality constraints, such as the active (or reactive) power balance and inequality, constraints such as the voltage limits, line and transformer current limits. A comprehensive review of the DG planning constraints is presented in [3] and more recently in [6].

The methods used in DG planning are classified in three groups as conventional, intelligent and fuzzy methods [3]. The most frequently used methods are based on a genetic algorithm [7]. The recent developments in this area are presented in reviews [8], [6] and [4]. Reference [9] presents a hybrid heuristic search optimisation technique for an optimal DG and shunt capacitor allocation for power loss minimisation in radial power distribution networks. Finally, a cuckoo search algorithm for determination of an optimal allocation and sizing of DG units considering the voltage stability, power losses and load variations is presented in [10]. The advantages of the artificial intelligence based optimisation methods are an efficient performance, need of fewer iterations, ability to analyse complex systems and substantial accumulation of the existing knowledge. Their disadvantages are complexity, premature convergence, instability, setting parameters, unstable results and uncertain convergence [6]. More specifically, genetic algorithms (GA) are a more desirable tool than the conventional methods because they do not require the continuity of the objective function. Their disadvantage is a possible premature convergence around the local minima region. For this reason and considering the fact that GA is a search technique, the GA search should be guided towards a specific region of a variable space in order improve the algorithm efficiency. Finally, taking into consideration the accumulated body of evidence, it can be concluded that DG allocation continues to be a vibrant and relevant research topic.

3 PROBLEM FORMULATION

In the paper, the optimisation problem is presented as a multi-objective constrained optimisation problem with three objectives and three constraints. The first objective function in this paper is the active power loss minimisation, formulated as follows:

$$min f_{loss} = \sum_i 3\,|I_i|^2 R_i \tag{1}$$

where f_{loss} is the power losses function and I_i, R_i are the current and resistance in the i^{th} branch, respectively.

The second objective function is the voltage drop minimisation. Speaking in terms of the voltage profile improvement, the objective of the optimisation problem is to find a solution to minimise the voltage drop at the location with the worst voltage profile. Mathematically, this objective is formulated as follows:

$$min\ f_{voltage} = \sqrt{\frac{P_{ij}\left(R_{ij}^2 + X_{ij}^2\right)}{R_{ij}}} \tag{2}$$

where $f_{voltage}$ is the voltage function, P_{ij}, R_{ij} and X_{ij} are the active power, resistance and reactance of the branch between nodes i and j, respectively.

The third objective is to maximise the number of years for which the distribution extension can be deferred due to DG allocation. This objective can be formulated as follows:

$$max f_y = \sum_i \frac{log P_{limit(i)} - \log(P_{\max(i)} - P_{dg(i)})}{log(1+\Delta P)} \tag{3}$$

where f_y is the deferment function, $P_{limit(i)}$ is the substation maximum capacity power, $P_{\max(i)}$ is the maximum power demand at the substation, $\Delta P = 0{,}1$ is the load increase rate, n is the number of years after which the capacity extension will be required and $P_{dg(i)}$ is the DG power output for the i^{th} load flow, as defined in more details in [11].

The first constraint used in this paper is the short circuit power constraint, imposed on DG by the system operator in order to limit fast voltage variations at the point of common coupling. Mathematically, for inverters it is defined as [11]:

$$\sum S_{ng} \leq \frac{S_{sc}}{25} \tag{4}$$

where S_{ng} is the DG rated power, S_{sc} is a three phase short circuit power at the DG point of connection. The second constraint used in this paper is the voltage limit constraint, which ensures that voltage levels remain within the required limits. It is defined as:

$$V_{min} \leq V_i \leq V_{max} \quad \forall i \in N \tag{5}$$

where V_i is the voltage value at node i, N is a set of power system nodes and contain the number of elements equal to the number of nodes under consideration, $V_{i,min}$ and $V_{i,max}$ are the minimum and maximum permissible voltage value at node. Finally, the third constraint is the power line current limit. Defining B as a set of power branches under consideration, the maximum line rating constraint is defined as:

$$I_j \leq I_{j,max} \quad \forall j \in B \tag{6}$$

where I_j is the current flowing through line j, B is a set of power branches under consideration, $I_{j,max}$ is the maximum permissible current value flowing through line j. The multi-objective optimisation problem can be formulated as the problem of finding the optimum of the following multi-objective function:

$$\mathrm{F} = \min\left(\sum_i 3\,|I_i|^2 r_i\right) + \min\left(\sum_{ij} \sqrt{\frac{P_{ij}\left(R_{ij}^2+X_{ij}^2\right)}{R_{ij}}}\right) + \max\left(\sum_i \sqrt{\frac{\log P_{limit(i)} - \log\left(P_{\max(i)} - P_{dg(i)}\right)}{\log(1+\Delta P)}}\right) \tag{7}$$

subject to conditions described in Equations (4)-(6).

4 Case Study

This section presents the results of the model application, discussion and some of the most important future tasks of our future research direction. First, the brief description of the test system is given. It is followed by the definition of the optimisation case and an outline of the computational procedure. The load flow result for the base case with no DG installed is then presented, followed by the results of the algorithm application. Finally, the plans of the future research directions are briefly outlined.

4.1 Model of the test power system

The test power system shown in Figure 1 represents a realistic system currently used in Bosnia and Herzegovina. It consists of the main 110/35/10 kV source substation which supplies eight 35/10(20) kV zone substation over 35kV underground cables and overhead lines. The test model is a good representation of a typical radial power distribution systems used to supply electricity to an urban area.

A detailed description of the parameters, including the loading conditions, is given in [12]. Table 1 represents the maximum power (S_{max}) in MVA values for each DG candidate location of the proposed test model.

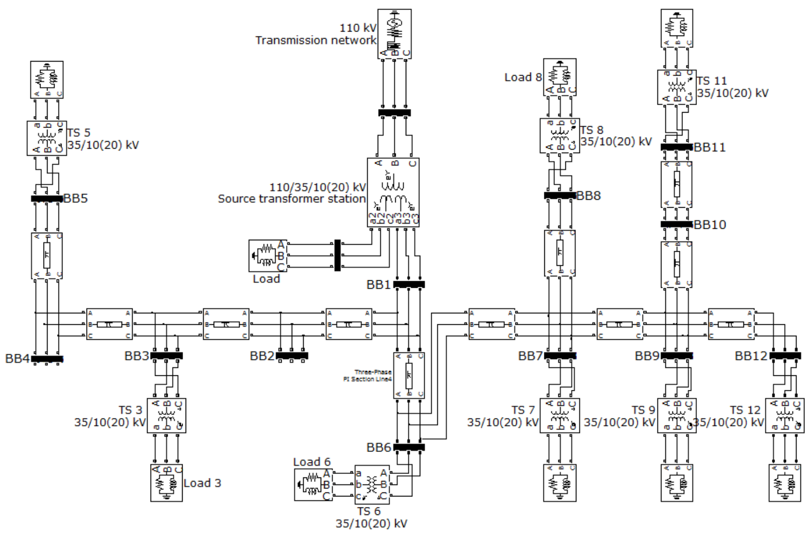

Figure 1. Model of the test power system

4.2 Formulation of the optimisation cases

The first step in the GA application is the definition of the chromosome, represented as an array. Each element of an array is a gene, which represents a variable that needs to be optimised. The 11 genes and the chromosome are represented as:

$$chromosome = [x_1, x_2, x_{3,}, \ldots, x_{11}] \qquad (8)$$

There is a total of 11 single gene values, represented in a double vector form. They can take any value in the interval [0-1]. The value of each gene is multiplied by the total power (S_{max}) permitted in that node. For example, the string of all zeros means that no DG is allocated in the system and the string of all ones represent a situation in which the maximum permitted DG power is installed at each node. Each chromosome carries the values of the objective functions in terms of the power loss, voltage and years as a function of variables x_1, x_2, …..x_{11}. The values of the objective functions are repeatedly calculated using the power flow analysis and assigned to a single chromosome. The genetic algorithms are normally set to determine the minimum of objective function F. In this problem, the third objective function needs to be maximised, and in order to search for the global maximum, objective function G to be maximised is set as G=-F.

4.3 Computational procedure

The calculations are performed on an Intel(R) Core (TM) i3 CPU M330 2.13 GHz architecture with 4 GB of the RAM memory, 64 bit OS. Figure 2 schematically describes the proposed computational procedure. The first step is to determine the values of the objective functions for the base case. They are calculated using the load flow for the existing network configuration. Then, at each of the eleven DG candidate locations the maximum permissible active power is multiplied by the values represented by a gene on a chromosome. The chromosome is a double type vector with the population size of 15 times the number of the variables. For each possible candidate, the values of the objective functions are computed using [13]. The Matlab Optimisation Toolbox (MOT) environment is used to run the genetic algorithm which is integrated with [13] providing the values of the fitness functions after each load flow analysis. The default values in MOT are used to set the parameters of the initial population, initial score and initial range. Finding the best compromise among the obtained solutions from the Pareto front is based on the Bellman–Zadeh fuzzy multi-criteria decision-making [14]. This approach is applied in numeorus engineering applications, such as [15].

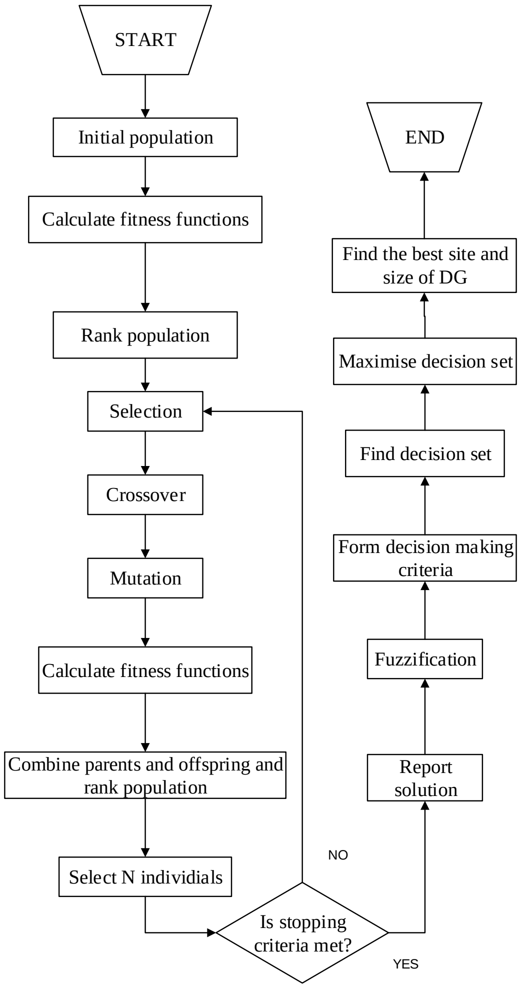

Figure 2. Outline of the computational procedure

4.4 Results and discussion

The power system losses for the base case with no DG in the system are 0.591 MW. Most of the losses are generated in the 1-6 line, which carries the largest current. The minimum voltage magnitude is 0.963 p.u. at the bus number 12. The number of years is 40.6. Compliably with the chromosome definition given in Section 4.2., this case is represented with a chromosome which has all the genes equalling zero.

The proposed algorithm with its three objective functions converges successfully and obtains a total of 58 candidate solutions for an optimal DG allocation. The candidate solutions are displayed in a three dimensional Pareto set shown in Figure 3. The range of the candidate solutions is:

$$P_{loss} = [0.053 - 0.264]\ MW \qquad (9)$$

$$V = [0 - 0.0079]\ p.u. \qquad (10)$$

$$n = [104.3 - 333.5]\ years \qquad (11)$$

In this range, the optimal system DG capacity is within the $[26.48 - 38.88\text{ MW}]$ interval. Figure 4 shows the total DG capacity for each of the 58 candidate solutions of the optimisation model. In order to obtain the best trade-off, the values are fuzzified and the fuzzy set intersection is determined as the minimum of two membership functions. The best configuration is calculated by determining the maximum value of the membership function of the fuzzy decision set (D), shown in [12], which in this case represents an alternative (A_{43}) and can be written as:

$$\mu_D(x^*) = \mu_{D_{43}}(\widetilde{x_{43}}) = 0.528939 \qquad (10)$$

Table 1 shows the output values of the algorithm for each candidate location in the second row. Compliably with Eq. (8), the best candidate solution is determined by a chromosome, which has its gene values shown in the second row of the Table 1. Finally P_{opt}, which is the optimal size for each candidate location is shown in the fourth row of Table 1. It is obtained by multiplying the value of each gene of the best solution with the S_{max} at the respective node. The simulation results show that the total optimal DG capacity of the system for the power loss reduction, voltage drop reduction and capacity extension deferral is $P_{tot} = 30.57$ MW which represents the sum of optimal DG capacities at each node. The load flow analysis for the case with the optimal DG site and size determined that the power system losses are $P_{loss} = 0.098$ MW, which represents significant decrease compared to the base load case. The minimum voltage magnitude is found to be $V = 0.996$ p.u. at bus 6 which means that there is virtually no voltage drop in the system. The time framework required for the capacity extension is extended from $n = 40.6$ to $n = 176.40$ years.

Considering the system load distribution and the DG allocation, it can be concluded that in the case of high penetration, the level of the DG dispersion is a critical factor for achieving the optimal results in terms of the power loss reduction, voltage profile improvement and capacity extension deferral. The high DG penetration levels combined with a low DG dispersion are likely to deteriorate power distribution network parameters. The optimal configuration does not achieve a single optimum solution for each objective function and because of that it is necessary to find the best compromise among several objectives. This means that in order to increase the extension time deferral, a higher DG penetration is required, which, after a certain point, inevitably leads to an increase in the power losses. This problem becomes more articulated with an increase in the number of the objective functions. For this reason, multi-objective problems with more than three objective functions are rare and need to be carefully designed. Apart from this, Pareto front visualisation becomes an issue when the number of the objectives is more than three because the representation of the points on the Pareto front becomes multi-dimensional. The choice of the number and type of the objectives is therefore an important decision-making challenge. For example, when the number of the objectives is reduced to two, it is possible to further improve the fitness of a single objective function. Decreasing the number of the objective functions leads to a faster algorithm convergence and improvement of a single objective, which leads to a reduction of the optimal DG capacity of the system. However, inclusion of more objective functions provides a more realistic insight into the system behaviour.

The presented objective functions do not exhaust the list of all the possible decision variables. The proposed model is flexible, which means that it can be extended to include additional decision-making objectives required by the decision maker. The system load and DG power output uncertainty also represent and important future research task because of their significant impact on the final optimisation result.

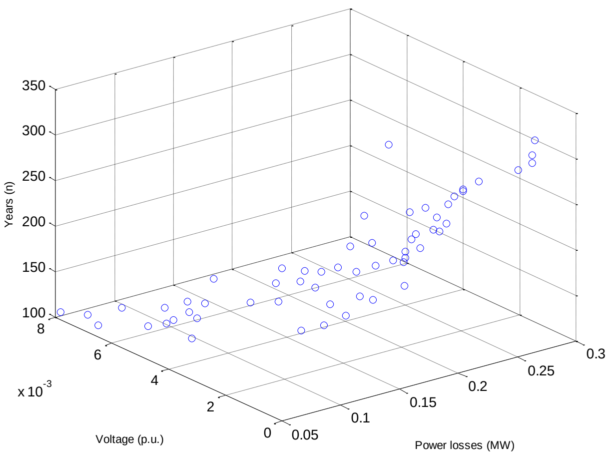

Figure 3. 3D representation of Pareto front

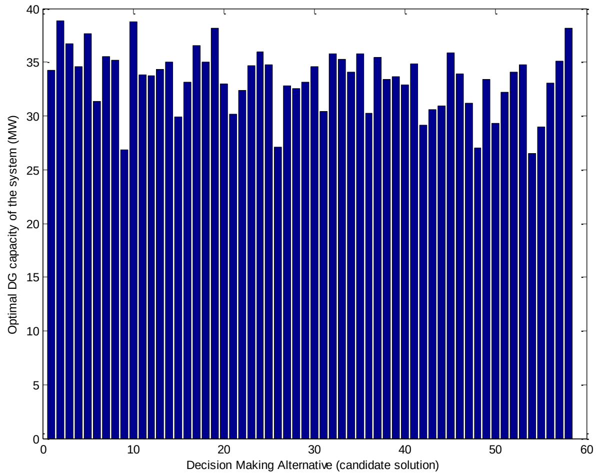

Figure 4. Total DG capacity for each candidate solution

Table 1. The output values of the algorithm for each candidate location

Node	2	3	4	5	6	7	8	9	10	11	12
GA_{out}	0.129	0.468	0.280	0.762	0.774	0.351	0.454	0.185	0.241	0.118	0.409
S_{max}(MVA)	11	7.56	8.02	6.62	9.02	7.56	7.52	6.82	6.16	4.6	4.9
P_{opt}(MW)	1.42	3.54	2.24	5.04	6.98	2.65	3.41	1.26	1.49	0.54	2.0

5 CONCLUSION

The paper presents a method for the DG allocation planning using a multi-objective genetic algorithm and fuzzy multi-criteria decision-making. The results demonstrate that DG has a potential to improve the network technical and economic parameters but its size and location need to be optimised using appropriate tools. The power losses tend to be minimised at DG medium penetration and high dispersion levels. They are maximised in the case of a low dispersion and high penetration scenario. DG has a potential to maximise the investment deferral in the case of configurations with dispersion concentrations that closely follow load concentrations. The increase in the number of objectives increases computational complexity and is likely to cause an inferior fitness of each single objective. The uncertainty of the power system load, generation output, construction timing and operational strategies are the parameters which considerably affect the optimisation results and their evaluation and should be researched in the future.

REFERENCES

[1] M. Esmaeili, M. Sedighizadeh and M. Esmaili, "Multi-objective optimal reconfiguration and DG (Distributed Generation) power allocation in distribution networks using Big Bang-Big Crunch algorithm considering load uncertainty",*Energy, Volume 103,* pp. 86-99, 2016.

[2] A. Bayat, A. Bagheri and A. Noroozian, "Optimal siting and sizing of distributed generation accompanied by reconfiguration of distribution networks for maximum loss reduction by using a new UVDA-based heuristic method", *Journal of Electrical Power & Energy Systems, Volume 77,* pp. 360-371, 2016.

[3] R. Payasi, A. Singh and D. Singh, "Review of distributed generation planning:objectives, constraints and algorithms", *International Journal of Engineering, Science and Technology, vol. 3, no. 3,* pp. 133-153, 2011.

[4] V. Theo, J. Lim, W. Ho, H. Hashim and C. Lee, "Review of distributed generation (DG) system planning and optimisation techniques: Comparison of numerical and mathematical modelling methods", *Renewable and Sustainable Energy Reviews, Volume 67,* pp. 531-573, 2017.

[5] S. Ikeda and R. Ooka, "A new optimization strategy for the operating schedule of energy systems under uncertainty of renewable energy sources and demand changes", *Energy and Buildings, Volume 125,* pp. 75-85, 2016.

[6] M. Pesaran, P. Huy and V. Ramachandaramurthy, "A review of the optimal allocation of distributed generation: Objectives, constraints, methods, and algorithms", *Renewable and Sustainable Energy Reviews, Volume 75,* pp. 293-312, 2017.

[7] P. Georgilakis and N. Hatziargyriou, "A review of power distribution planning in the modern power systems era: Models, methods and future research“, *Electric Power Systems Research, Volume 121,* pp. 89-100, 2015.

[8] A. Jordehi, "Allocation of distributed generation units in electric power systems: A review", *Renewable and Sustainable Energy Reviews, Volume 56,* pp. 893-905, 2016.

[9] K. Muthukumar and S. Jayalalitha, "Optimal placement and sizing of distributed generators and shunt capacitors for power loss minimization in radial distribution networks using hybrid heuristic search optimization technique", *International Journal of Electrical Power and Energy Systems, Volume 78,* pp. 299-319, 2016.

[10] B. Poornazaryan, P. Karimyan, G. Gharehpetian and M. Abedi, „Optimal allocation and sizing of DG units considering voltage stability, losses and load variations", *Journal of Electrical Power & Energy Systems, Volume 79,* pp. 42-52, 2016.

[11] M. Saric, J. Hivziefendic and T. Konjic, "Distributed Generation Allocation Using Fuzzy Multi Criteria Decision Making Algorithm", *International Conference on Smart Systems and Technologies 2017 (SST 2017)*, Osijek, Croatia,, 2017.

[12] M. Saric, J. Hivziefendic, T. Konjic and A. Ktena, "Distributed generation allocation considering uncertainties*", International Transactions on Electrical Energy Systems, vol. 28, no 9, 2018*

[13] R. Zimmerman, C. Murillo-Sánchez and R. Thomas, "MATPOWER: Steady-State Operations, Planning and Analysis Tools for Power Systems Research and Education“, *Power Systems, IEEE Transactions on, vol. 26, no. 1,* pp. 12-19, 2011.

[14] R. Bellman and L. Zadeh, "Decision-making in a fuzzy environment", *Management Science Vol 17 no.4,* Bellman and Zadeh, “Decision-making in a fuzzy environment”, Management Science, Vol 17, NO.4, December 1970 December 1970.

[15] M. Saric and J. Hivziefendic, "Management of the Power Distribution Network Reconstruction Process Using Fuzzy Logic", in *Advanced Technologies, Systems, and Applications* , Springer Int. Publ., 2017, pp. 155-172.

Mirza Šarić received his Ph.D. degree in Electrical and Electronics Engineering from the International Burch University, Sarajevo, Bosnia and Herzegovina, in 2018. He works as an assistant professor at the Department of Electrical and Electronic Engineering, at the International Burch University. His research interests are in electrical power distribution system planning and operation.

Jasna Hivziefendić received her Ph.D. degree in Electrical Engineering from the University of Tuzla, Bosnia and Herzegovina, in 2014. She works as an associate professor at the Department of Electrical and Electronic Engineering at the International Burch University, Sarajevo. Her research interests are in electrical power distribution system planning, distributed power generation and optimisation.

Tatjana Konjić received her Ph.D. degree in Electrical Engineering from the Faculty of Electrical Engineering, University of Tuzla, Bosnia and Herzegovina in 2003. She works as a professor at the University of Tuzla and University of Sarajevo. Her research interests are in application of computation intelligence to power systems, distributed power generation and power quality.