A Tabu Search Method for Distribution Network Planning Considering Distributed Generation and Uncertainties

N. C. Koutsoukis, P. S. Georgilakis, and N. D. Hatziargyriou
School of Electrical and Computer Engineering
National Technical University of Athens (NTUA)
Athens, Greece
{koutsoukis, pgeorg, nh}@power.ece.ntua.gr

***Abstract*—This paper deals with the problem of distribution network planning (DNP) considering distributed generation (DG) and uncertainties. The involved uncertainties are the output power of wind and PV generation, the future load growth in the planning period and the evolution of the electricity prices. A Tabu search (TS)–based method with an embedded probabilistic power flow analysis is developed in order to solve the DNP optimization problem. The probabilistic power flow problem is solved by Monte Carlo Simulation (MCS). The proposed method is applied to a benchmark system and to a 30-bus distribution network considering several scenarios to demonstrate the method's performance and robustness. Simulation results show how the network planning is affected from the considered uncertainties and the optimal network is rather different in comparison to the networks designed via a conventional approach without DG integration.**

Keywords—Distribution network planning, Tabu search, non-dispatchable distributed generation, Monte Carlo simulation, uncertainties, network optimization.

I. INTRODUCTION

With the increase of power demand due to technological and industrial development and the need of meeting clean energy targets with the implementation of renewable energy sources, distribution network planning (DNP) becomes a significant and complex problem. The main objective of the DNP problem is to design the distribution system such as to timely meet the demand growth in the most economical, reliable, and safe manner possible. The efficient design of such networks should take into account the involved uncertainties, such as the load evolution within the planning horizon and the uncertain output power of the non-dispatchable distributed generation (DG) in the network. For example, the underestimation of the load growth may have as an impact the need for additional reinforcement and expansion, which means extra costs for the distribution network operator.

A variety of models and methods have been proposed for the solution of distribution network planning problem [1]. The most common meta-heuristic optimization methodologies for solving the DNP problem are the Genetic Algorithm (GA), Simulated Annealing (SA), Ant Colony System (ACS) and Evolutionary Algorithms (EA) [2]–[5]. Tabu Search (TS) algorithm has also been proposed for solving the DNP problem considering fuzzy conditions [6], [7]. In [8], the proposed Immune System Algorithm solves the DNP problem taking into account the uncertainties of the load growth evolution and the energy tax. In all the aforementioned research works, it is considered that the power flow is unidirectional, from the distribution substation to the load buses through the feeders, and the DNP problem is solved by upgrading or adding new distribution lines and by expanding the capacity of a substation or building new ones, as the load grows.

An efficient way to minimize the power losses and to defer the investment in new lines is the installation of DG units in the power distribution network [9]. However, this depends on the optimal planning (type, location, and size) of the DG units. In many cases, inappropriate DG planning may increase network losses and operating and capital costs. A planning method [10] incorporates dispatchable DG (DDG) for the minimization of power losses in a distribution system. A dynamic ACS [11] also considers DG, such as gas micro turbines, for the expansion and reinforcement of the distribution network. In [12] and [13], a branch and bound method examines the DG as an option for meeting the load growth. A DNP strategy based on the Particle Swarm optimization algorithm, which takes into consideration the DDG output power, is presented in [14]. In [15], the proposed DNP method considers the uncertainties of the future load demand and the output power of DG units in the optimization procedure.

This paper introduces a novel method for solving the DNP problem considering the integration of non-dispatchable DG units, such as wind and PV generation, in the power distribution network, under uncertainties. The proposed methodology is based on the Tabu Search algorithm and it deals with the optimization of the network topology configuration subject to technical and operational constraints. A Monte Carlo simulation (MCS) is employed to solve the embedded probabilistic power flow analysis.

This paper is organized as follows. In Section II, the modeling of the uncertainties is presented. Section III formulates the optimization problem and Section IV describes the proposed methodology. In Section V, the method is applied to a benchmark system and to a 30-bus distribution network and the obtained results verify the efficiency and validity of the method. Section VI concludes the paper.

II. Modeling of Uncertainties

A. Output-Power Uncertaintity of the Wind turbines

It is experimentally well-established that the stochastic wind speed (v) can be described by the Weibull probability density function (PDF) [16]:

$$f(v)=\frac{k_w}{c_w^{k_w}}v^{k_w-1}exp\left(-\left(\frac{v}{k_w}\right)^{k_w}\right) \quad , \quad 0\leq v<\infty \tag{1}$$

where k_w and c_w are the shape and scale index, respectively, of the Weibull distribution. Once the Weibull PDF of wind speed is generated, the output power of a wind turbine for its different states can be calculated as follows [16]:

$$P_W=\begin{cases} 0 & , \quad 0\leq v\leq v_{ci} \\ P_{Wn}\dfrac{(v-v_{ci})}{(v_n-v_{ci})} & , \quad v_{ci}\leq v\leq v_n \\ P_{Wn} & , \quad v_n\leq v\leq v_{ci} \\ 0 & , \quad v_{co}<v \end{cases} \tag{2}$$

where P_{Wn} is the nominal output power of the wind turbine and v_{ci}, v_{co}, v_n, are the cut-in wind speed, the cut-out wind speed and the nominal wind turbine speed, respectively.

B. Output-power Uncertaintity of the PV module

The output power of a photovoltaic module mainly depends on the solar illumination intensity (s) that follows the Weibull distribution with the following PDF [17]:

$$f(s)=\frac{k_s}{c_s^{k_s}}s^{(k_s-1)}\exp\left(-\left(s/c_s\right)^{k_s}\right) \quad , \quad 0\leq s<\infty \tag{3}$$

where k_s and c_s are the shape and scale index, respectively, of the Weibull distribution. The output power of a PV module considering the illumination intensity is given by:

$$P_S=\begin{cases} P_{Sn}\dfrac{s}{s_n} & , \quad 0\leq s\leq s_n \\ P_{Sn} & , \quad s_n\leq s \end{cases} \tag{4}$$

where P_{Sn} is the nominal output power of the PV module and s_n is its nominal solar illumination intensity.

C. Load Growth Uncertaintity

As a consequence of the technological and industrial development, the power demand is increasing. It is considered that the load growth $\Delta P_{Li}(t)$ of the bus i in the year t of the planning period follows the normal distribution with mean value $\mu_i(t)$ and standard deviation $\sigma_i(t)$ and thus the load $P_{Li}(t)$ is given by [17] :

$$P_{Li}(t)=P_{Li}(t-1)+\Delta P_{Li}(t) \tag{5}$$

D. Electricity Price Uncertaintity

The electricity price C_L is also modeled under uncertainties and is supposed to follow the normal distribution, which means $\Delta C_L(t)\sim N(\mu_L(t),\sigma_L^2(t))$.

III. Problem Formulation

The distribution network planning problem can be stated as a nonlinear combinatorial optimization problem, where the main objective is the minimization of the fixed cost associated to the installation of new distribution lines and DG units and the variable costs including the cost of buying energy from the transmission system, the power loss cost, and the maintenance cost, subject to technical and operational constraints. This means that it is considered that all the DGs are owned by the distribution system operator. However, in case that all the DGs are owned by private investors, the investment and maintenance costs of DG units have to be excluded from the objective function.

A. Objective function

The objective function is formulated as follows:

$$\begin{aligned} \min\ f &= C^{IL}+C^{I}+C^{M}+C^{L}+C^{B} \\ &=\sum_{b=1}^{N_b}C_{ILb}+\sum_{i=1}^{N_{DG}}\frac{1}{(1+n)^{T_{inv}}}C_{DGi}^{I}P_{DGi}^{N}+\sum_{t=1}^{T}\frac{1}{(1+n)^{t}} \\ &\left\{\sum_{i=1}^{N_{DG}}\left(C_{DGi}^{M}T_{DGi}(t)P_{DGi}^{N}(t)\right)+C_L(t)W_{loss}(t)+C_L(t)\left(W_S(t)-W_{DG}(t)\right)\right\} \end{aligned} \tag{6}$$

where,

- n is the discount rate;
- T is the number of years of the planning period;
- T_{inv} is the year when DG units are installed;
- $C^{IL}, C^{I}, C^{M}, C^{L}$ and C^{B} are the investment cost of distribution lines, the DG investment cost, the DG maintenance cost, the network's loss cost and the cost of buying energy from the transmission system, respectively;
- N_b is the total number of network's branches;
- N_{DG} is the number of the installed DG units;
- $W_{loss}(t)$ is the energy loss in year t (kWh);
- $W_S(t)$ is the energy demand in year t (kWh);
- $W_{DG}(t)$ is the energy supplied from the installed DG units in year t (kWh);
- $P_{DGi}^{N}(t)$ is the nominal output power of the i-th DG unit installed in year t;
- $T_{DGi}(t)$ is the equivalent generation hours of the i-th DG unit installed in year t;
- C_{ILb} is the cost of branch b of the network ($);
- C_{DGi}^{I} is the per unit investment cost of the i-th DG unit ($/kW);
- C_{DGi}^{M} is the per unit maintenance cost of the i-th DG unit ($/kW);

- $C_L(t)$ is the electricity price in year t ($/kWh);

B. Constraints

1) *Radial network connectivity constraint*. The radial characteristic of the network and the connectivity of all network nodes are ensured by the proposed branch selection movement described in Section IV.B.
2) *Power flow equations*. The Newton–Rhapson method is employed to solve the power flow problem described by equations (7), (8) for every input stochastic variable:

$$P_{Li} = V_i \sum_{j=1}^{N_{AD}} V_j \left(G_{ij} \cos\delta_{ij} + B_{ij} \sin\delta_{ij} \right) \tag{7}$$

$$Q_{Li} = V_i \sum_{j=1}^{N_{AD}} V_j \left(G_{ij} \sin\delta_{ij} - B_{ij} \sin\delta_{ij} \right) \tag{8}$$

where, P_{Li}, Q_{Li} are the active and reactive power of the demanded load at bus i; V_i, V_j are the voltage magnitudes at buses i and j; N_{AD} is the total number of the adjacent buses of bus i; G_{ij}, B_{ij} are the conductance and susceptance between bus i and j; δ_{ij} is the voltage angle between buses i and j.
3) *Voltage regulation limits*. For the safe operation of the network the voltage level of every bus i must be kept into specific limits:

$$V_{\min} \le V_i \le V_{\max} \tag{9}$$

4) *Capacities of distribution lines*. For every existing feeder in the network its thermal capacity limit cannot be violated:

$$S_{ij} \le S_{ij\max} \tag{10}$$

IV. Solution Methofology

The distribution network planning problem addressed in this paper concerns the optimization of a newly network configuration considering DG connection under the uncertainties described in Section II. The meta-heuristic Tabu Search (TS) algorithm, with an embedded Monte Carlo Simulation (MCS), is proposed for the solution of the problem in order to reach the optimal planning solution subject to the constraints of Section III.B.

A. Tabu Search Overview

Tabu search (TS) is a meta-heuristic algorithm ideal for solving a wide range of combinatorial optimization problems and it was introduced and established by Glover [18].

TS is a memory-based iterative method, which creates, by using specified movements, a neighborhood $N(x)$ of the solution x and evaluates the neighbor solutions with an objective function $f(x)$. Considering a minimization problem, TS selects the neighbor solution x' with the smallest value to continue the search. A memory mechanism named Tabu list (TL) records the movements that created the previous solutions, which is referred to as tabu active moves, and it restricts the choice of previously visited solutions for a certain number of iterations. Thus, the entrapment in local optima is avoided. Tabu restrictions are overridden only when a candidate tabu move yields a solution that its value is better than any visited solutions so far. This condition is called Aspiration criterion. TS is terminated when a stop criterion, e.g. a pre-specified number of iterations, is satisfied.

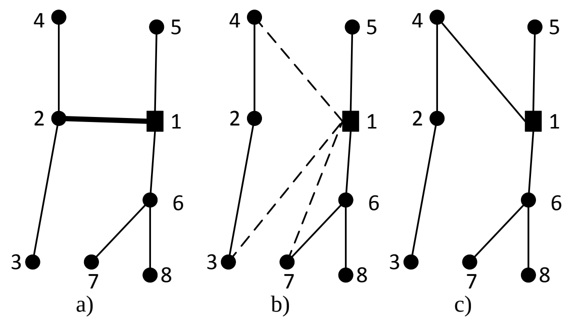

Fig. 1. Example of TS movement strategy.

B. Network Configuration Topology

In this paper, TS is employed for finding the best topology of feeders subject to the constraints presented in Section III.B, in order to satisfy the power demand in every bus during the planning period and minimize the total investment and operation cost. The method is formulated as follows:

Step 1: Kruskal's minimum spanning tree algorithm is used for the generation of an initial solution. For a given network with all possible feasible routes, Kruskal's algorithm, through an iterative procedure, adds to the network's topology the feeder with the lowest investment cost that does not violate the radiality constraint, until all nodes are connected. This solution ensures the radiality of the network and it is accepted even if some other constraints are violated, since new solution without infeasibilities will be generated through the next steps of the optimization process.

Step 2: No tabu active moves are considered, thus the Tabu list is empty.

Step 3: MCS is employed for the probabilistic power flow analysis of the initial solution of Step 1 and the value of (6) is calculated. The initial solution is stored as the current solution.

Step 4: A set of candidate solutions is created based on the network topology of the current solution. The movement that creates the candidate solutions is the elimination of a feeder that connects two nodes and then the addition of a new feeder with the same features that ensures the radiality of the network. An illustrative example is given in Fig. 1. Fig. 1(a) presents a distribution network in which bus 1 is the slack bus (substation), while the rest of the buses are load buses and the continuous lines represent the existing feeders. The feeder (1,2) is to be eliminated and Fig. 1(b) shows the candidate feeders, marked by dashed lines, which are to be added. From the candidate feeders only (1,3), (1,4) are feasible, since (1,7) does not allow the connectivity of all nodes. Let us suppose that the branch (1,4) is selected and a new radial network topology is created, as shown in Fig. 1(c).

Step 5: Every feasible candidate solution is evaluated by (6).

Step 6: Choose as new current solution the best solution from the set of the candidate solutions, which does not contain

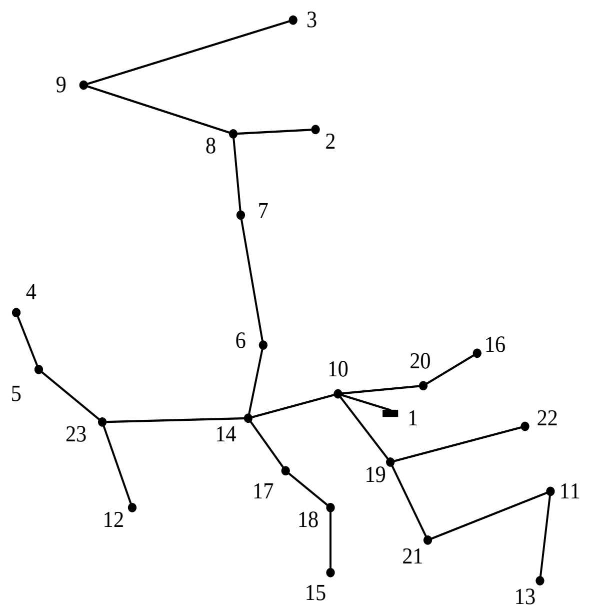

Fig. 2. Solution obtained by the proposed TS for the benchmark network.

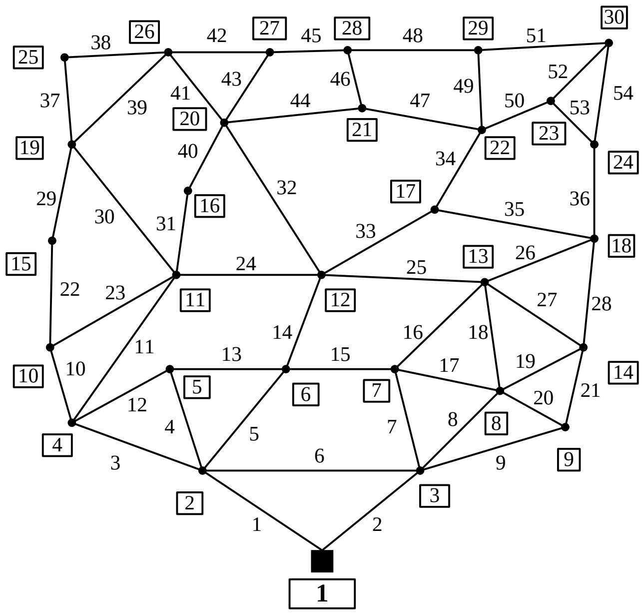

Fig. 3. Graph of the 54 candidate routes for the design of the 30-bus network.

a tabu active move. Tabu restrictions are overridden in case the value of the best solution of the candidate set is better than the best solution found so far (Aspiration Criterion).

Step 7: Tabu List is updated and the movement that created the new current's solution network topology is restricted for a certain number of iterations.

Step 8: When a specified number of global iterations has been carried out, TS is terminated returning the best solution found during the search, else Steps 3–9 are repeated.

V. Results and Discussion

The proposed method was implemented in Matlab 7.9 and a PC Intel® Core i3 3.07 GHz, 4GB RAM was used to obtain the numerical results.

A. Benchmark Case Study

The proposed method is initially tested on the 23-bus benchmark distribution network, the data of which can be found in [4], in order to investigate the performance of the TS method. This case study concerns a distribution network supplied by a 10MVA substation, with 21 load nodes, while uncertainties are not considered. The planning period is 20 years and two types of conductors have been considered in the design.

The TS iterations were equal to 50 and the size of the Tabu list was 6. The obtained solution is presented in Fig. 2 and its topology is identical to the solution of [3], [4]. The solution costs $172 445 and the total CPU time is 7.23 s.

B. The 30-bus Distribution System

A 34.5-kV distribution network with 30 buses and 1.2 MW of DG to be installed is considered for the demonstration of the performance and robustness of the proposed method. The case study network includes a slack bus at bus 1 and 29 load buses. The original load consumption at each bus is presented in Table I. There are 54 candidate distribution line routes as shown in Fig. 3 and their data are presented in Table II. All lines are considered overhead and in the planning process two conductor types are considered, whose technical and economic data are shown in Table III. The total load of the network is 5.74 MVA and the average power factor is 0.9. The voltage of slack bus is considered $V_1 = 1.0$ p.u. The voltage magnitude deviation is allowed within ±5% of the nominal voltage for all the load buses. The load profile of the system is shown in Table IV. Table V shows the planning scheme for the future installation of the DG units in the network. The load growth

TABLE I. Original Consumption at Load Buses

Load bus no	2	3	4	5	6	7	8	9
Load (kVA)	250	250	300	120	120	500	500	120
Load bus no	10	11	12	13	14	15	16	17
Load (kVA)	120	100	120	120	220	120	120	120
Load bus no	18	19	20	21	22	23	24	25
Load (kVA)	200	200	200	200	200	200	250	250
Load bus no	26	27	28	29	30			
Load (kVA)	120	120	120	240	240			

TABLE II. Branch Length Data

Branch No.	2	3	4	5	6	7	8
Length (km)	1.55	2.20	1.65	2.10	1.50	2.00	1.05
Branch No.	9	10	11	12	13	14	15
Length (km)	1.05	0.75	1.75	1.75	0.40	1.75	1.00
Branch No.	16	17	18	19	20	21	22
Length (km)	1.00	1.00	1.25	1.00	0.75	1.50	1.75
Branch No.	23	24	25	26	27	28	29
Length (km)	1.75	2.00	2.00	1.05	0.65	1.75	1.25
Branch No.	30	31	32	33	34	35	36
Length (km)	0.45	2.75	1.75	1.75	0.50	0.75	0.50
Branch No.	37	38	39	40	41	42	43
Length (km)	0.50	1.25	0.75	1.50	0.75	0.50	0.40
Branch No.	44	45	46	47	48	49	50
Length (km)	1.10	0.60	1.20	0.60	0.55	0.40	1.00
Branch No.	51	52	53	54			
Length (km)	0.55	1.15	0.60	1.00			

TABLE III. TECHNICAL AND ECONOMIC DATA OF CANDIDATE LINES

Type	Impedance (Ω/km)	Nominal Power (MVA)	Investment Cost ($/km)
1	$0.5762+j0.5184$	8.96	10 000.00
2	$0.4724+j0.2875$	13.74	15 000.00

TABLE IV. LOAD PROFILE

Period	Load (p.u.)	Duration (h)
Peak Load	1.00	30
Average Load	0.70	5260
Minimum Load	0.45	3470
	Total	8760

TABLE V. PLANNING SCHEME OF DISTRIBUTED GENERATION INSTALLATION

Bus no	Year t=5		Year t=10		Year t=15	
	Wind DG (kW)	*PV DG (kW)*	*Wind DG (kW)*	*PV DG (kW)*	*Wind DG (kW)*	*PV DG (kW)*
12	100	100	0	0	0	0
19	0	200	0	200	0	100
30	200	0	200	0	100	0

TABLE VI. ECONOMIC DATA

Cost component	DG type	
	Wind turbine	*Photovoltaic*
Investment Cost C_I ($/kW)	1800	2000
Maintenance Cost C_M ($/kW)	0.05	0.03
Electricity Price C_L ($/kWh)	0.05	
Interest rate	10%	
Planning period (year)	20	

rates have been considered the same for all loads: the mean load growth is 2%, while the standard deviation of the load growth is 1%. The electricity prices are also increasing every year with mean value 2% and standard deviation 1%. In addition, the economic data required for the analysis is presented in Table VI. The duration of the planning period is 20 years and the discount rate is 10%.

Three scenarios are investigated. Scenario 1 examines the effect of not considering the planned DG installations for the solution of the DNP problem. Scenarios 2 and 3 examine the effect of the uncertain DG output power (different Weibull parameters) on the results. These parameters along with the technical features of the DGs are presented in Table VII.

The TS iterations for the three scenarios were equal to 80 and the size of the TL was 5. To obtain more reliable and accurate results, the MCS method was executed 300 times.

Table VIII presents a summary of the obtained results for the three Scenarios. The energy supplied from the transmission

TABLE VII. WEIBUL PARAMETERS AND TECHNICAL SPECIFICATIONS OF DG UNITS

DG Type	Scenario	Weibull Parameters		Technical specifications
		k (shape index)	*c* (scale index)	
Wind turbines	2	2	7.5	v_{ci} = 4 m/s v_{co} = 25 m/s v_n = 15 m/s Power factor = 0.9
	3	1.8	6	
PV module	2	1.5	5.5	s_n = 1000 W/m^2 Power factor = 1.0
	3	1.8	6.5	

TABLE VIII. SUMMARY OF RESULTS FOR SCENARIOS 1, 2 AND 3

	Scenario 1	Scenario 2	Scenario3
Distribution Lines Investment Cost ($)	277 500	326 000	326 000
DG Investment Cost ($)	0	1 091 800	1 091 800
DG Maintenance Cost ($)	0	549 490	503 110
Cost of Losses ($)	180 080	155 060	157 000
Cost of Buying Energy ($)	19 816 500	17 600 000	17 888 000
Total Cost ($)	20 274 080	19 722 350	19 965 910

network during the planning period for the Scenarios 1 and 2 is presented in Fig. 5. It can be seen from Table VIII that the network configuration of Scenario 2 (and Scenario 3) has a higher investment cost compared to the solution of Scenario 1, however Scenario 2 manages the output power of DG more efficiently, thus the total cost of losses is lower. The main difference between the cost of Scenario 1 and 2 is the cost of buying energy, since the installation of DG in Scenario 2 decreases the energy that is bought from the transmission system. Scenario 2 yields the solution with the lowest total cost. The values of the Weibull parameters of the DG units affect their output power. In Scenario 3 the proposed method yields a solution with the same network configuration with the solution of Scenario 2. The investment costs in both Scenarios are the same, however their difference can be found in the variable costs. In Scenario 3, the total output power of DG units is lower, thus the cost of losses and the cost of buying energy are slightly higher. The optimal network configuration of Scenarios 2 and 3 is presented in Fig. 4.

IV. CONCLUSION

In this paper, a new approach, based upon TS algorithm, is proposed for the optimal design of distribution networks incorporating non dispatchable DG units and considering uncertainties. The methodology minimizes the investment and operation cost of the network, subject to technical and operational constraints for meeting the demand, the voltage magnitude at all buses, the feeders' capacity and the radial configuration of the system. The uncertainties that are taken into account are the stochastic output power of the wind generators and the photovoltaics, the evolution of the load and the growth of electricity price. A Monte Carlo simulation is performed to solve the probabilistic power flow analysis. The application of the proposed methodology on a benchmark syst-

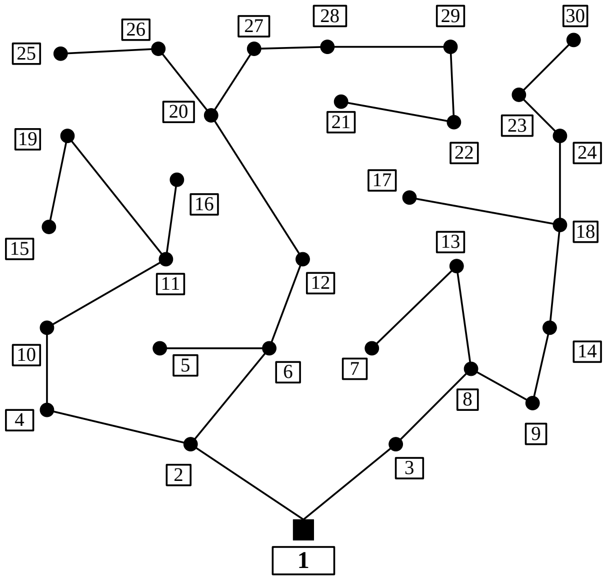

Fig. 4. Optimal network configuration for Scenario 2.

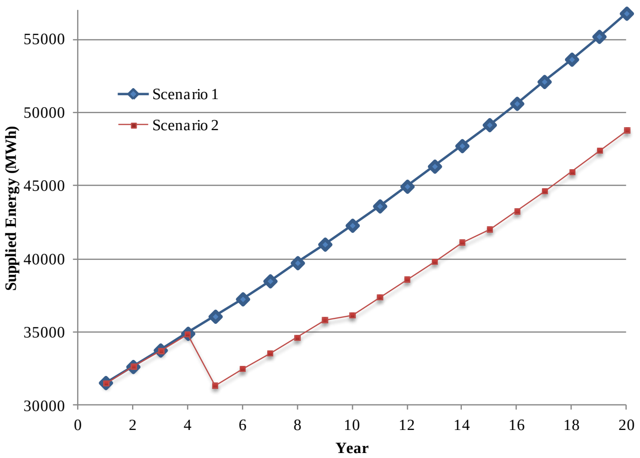

Fig. 5. Energy supplied (MWh) from the transimission system for Scenario 1 and 2 during the planning period.

em and on a 30-bus system with 1.2 MW of renewable energy sources showed the flexibility and effectiveness of the proposed method for solving the DNP problem at a low computational effort.

ACKNOWLEDGEMENTS

This work has been performed within the European Commission (EC) funded SuSTAINABLE project (contract number FP7-ENERGY-2012.7.1.1-308755). The authors wish to thank the SuSTAINABLE partners for their contributions and the EC for funding this project.

REFERENCES

[1] S. K. Khator and L. C. Leung,, “Power distribution planning: a review of models and issues,” IEEE. Trans. Power Syst., vol. 12, pp. 1151–1159, Aug. 1997.

[2] V. Miranda, J. V. Ranito, and L. M. Proença, “Genetic algorithm in optimal multistage distribution network planning,” IEEE Trans. Power Syst., vol. 9, no. 4, pp. 1927–1933, Nov. 1994..

[3] J. M. Nahman and D. M. Peric, “Optimal planning of radial distribution networks by simulated annealing technique,” IEEE Trans. Power Syst., vol. 23, no. 2, pp. 790–795, May 2008.

[4] J. F. Gómez, H. M. Khodr, P. M. Oliveira, L. Ocque, J. M. Yusta, R. Villasana, and A. J. Urdaneta, “Ant colony system algorithm for the planning of primary distribution circuits,” IEEE Trans. Power Syst., vol. 19, no. 2, pp. 996–1004, May 2004.

[5] E. Díaz-Dorado, J. Cidrás, and E. Míguez, “Application of evolutionary algorithms for the planning of urban distribution networks of medium voltage,” IEEE Trans. Power Syst., vol. 17, no. 3, pp. 879–884, Aug. 2002.

[6] I. J. Ramirez Rosado and J. A. Dominguez-Navaro, “Possibilistic model based on fuzzy sets for the multiobjective optimal planning of electric power distribution networks,” IEEE Trans. Power Syst., vol. 19, no. 4, pp. 1801–1810, Nov. 2004.

[7] I. J. Ramirez Rosado and J. A. Dominguez-Navaro, “New multiobjective tabu search algorithm for fuzzy optimal planning of distribution systems,” IEEE Trans. Power Syst., vol. 21, no. 1, pp. 224–233, Feb. 2006.

[8] E. G. Carrano, F. G. Guimaraes, R. H. C. Takahashi, O. M. Neto, and F. Campelo, “Electric distribution network expansion under load-evolution uncertainty using an immune system inspired algorithm,” IEEE Trans. Power Syst., vol. 22, no. 2, pp. 851–861, May 2006.

[9] P.S. Georgilakis and N.D. Hatziargyriou, “Optimal distributed generation placement in power distribution networks: Models, methods, and future research,” IEEE Trans. Power Syst., vol. 28, no. 3, pp. 3420–3428, Aug. 2013.

[10] W. El-Khattam, Y. G. Hegazy, and M. M. A. Salama, “An integrated distribution generation optimization model for distribution system planning,” IEEE Trans. Power Syst., vol. 20, no. 2, pp. 1158–1165, May 2005.

[11] S. Favuzza, G. Graditi, M. G. Ippolito, and E. R. Sanseverino, “Optimal electrical distribution systems reinforcement planning using gas micro turbines by dynamic ant colony search algorithm,” IEEE Trans. Power Syst., vol. 22, no. 2, pp. 580–587, May 2007.

[12] S. Haffner, L. F. A. Pereira, L. A. Pereira, and L. S. Barreto, “Multistage model for distribution expansion planning with distributed generation—part I: Problem formulation,” IEEE Trans. Power Del., vol. 23, no. 2, pp. 915–923, Apr. 2008.

[13] S. Haffner, L. F. A. Pereira, L. A. Pereira, and L. S. Barreto, “Multistage model for distribution expansion planning with distributed generation—part II: Numerical results,” IEEE Trans. Power Del., vol. 23, no. 2, pp. 924–929, Apr. 2008.

[14] I. Ziari, G. Ledwich, A. Ghosh, and G. Platt, “Optimal distribution network reinforcement considreing load growth, line loss, and reliability,” IEEE Trans. Power Syst., vol. 28, no. 2, pp. 587–597, May 2013.

[15] H. M. Khodr, Z. A. Vale, and C. Ramos, “A benders decomposition and fuzzy multicriteria approach for distribution networks remuneration considering DG,” IEEE Trans. Power Syst., vol. 24, no. 2, pp. 1091–1101, May 2009.

[16] Y. M. Atwa, E. F. El-Saadany, M. M. A. Salama, and R. Seethapathy, “Optimal renewable resources mix for distribution system energy loss minimization,” IEEE Trans. Power Syst., vol. 25, no. 1, pp. 360–370, Feb. 2010.

[17] V. A. Evangelopoulos and P. S. Georgilakis, “Optimal distributed generation placement under uncertainties based on point estimate method embedded genetic algorithm,” IET Gener. Transm. Distrib., article in press.

[18] F. Glover and M. Laguna, Tabu search. Kluwer Academic Publishers, CA: University Science, 1989.