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Authors(s)	Soroudi, Alireza, Rabiee, Abbas, Keane, Andrew
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Distribution Networks' Energy Losses Versus Hosting Capacity of Wind Power in the Presence of Demand Flexibility

Alireza Soroudi, Abbas Rabiee, Andrew Keane

Abstract

With the increasing share of renewable energy sources (RES) in demand supply, the distribution network operators (DNOs) are facing with new challenges. In one hand, it is desirable to increase the ability of the network in absorbing more renewable power generation units (or increasing the hosting capacity (HC)). On the other hand, power injection to the distribution network by renewable resources may increase the active power losses (if not properly allocated) which reduces the efficiency of the network. Thus, the DNO should make a balance between these two incommensurate objective functions. The Demand Response (DR) in context of smart grids can be used by DNO to facilitate this action. This paper provides an approach in which a multi-objective and multi-period NLP optimization model is formulated where the DR is utilized as an effective tool to increase HC and decrease the energy losses simultaneously. In order to quantify the benefits of the proposed method, it is applied on a 69-bus distribution network. The numerical results substantiate that the proposed approach gives optimal locations and capacity of RES, as well as minimum energy losses by load shifting capability provided via DR programs.

Index Terms

Demand response (DR), hosting capacity (HC), total energy losses, wind energy.

I. NOMENCLATURE

A. Sets and indices

i, j	Index of distribution network nodes
sb	Index of slack bus
t	Index of operating periods

Alireza Soroudi and Andrew Keane are with the School of Electrical, Electronic and Communications Engineering, University College Dublin, (e-mail: alireza.soroudi@ucd.ie, andrew.keane@ucd.ie). The work of A. Soroudi was conducted in the Electricity Research Centre, University College Dublin, Ireland, which is supported by the Commission for Energy Regulation, Bord Gáis Energy, Bord na Móna Energy, Cylon Controls, EirGrid, Electric Ireland, EPRI, ESB International, ESB Networks, Gaelectric, Intel, SSE Renewables, UTRC and Viridian Power & Energy. A. Soroudi is funded through Science Foundation Ireland (SFI) SEES Cluster under grant number SFI/09/SRC/E1780.

A. Rabiee is with the Department of Electrical Engineering, Faculty of Engineering, University of Zanjan, Zanjan, Iran, (e-mail: rabiee@znu.ac.ir)

24	ℓ	Index of distribution network feeders
25	Ω_n	Set of distribution network nodes
26	Ω_T	Set of operating periods
27	Ω_L	Set of distribution network feeders
28	Ω_{DR}	Set of distribution nodes participating in DR program
29	Ω_{sb}	Set of substation nodes in distribution network
30	Ω_D	Set of demand nodes in distribution network
31	Ω_W	Set of candidate distribution nodes for wind turbine installation

32 B. Parameters

33	Λ_i	Binary parameter indicating the participation of node i in DR
34	$\bar{I}_\ell$	Current capacity of line ℓ .
35	τ_t	Duration of time period t
36	$\zeta_{i,t}^w$	Forecasted (expected) power generation of wind turbine for time interval t in node i .
37	$P_{sb,min/max}$	Maximum/minimum active power injected to the distribution network from upstream grid in time interval t .
38	$Q_{sb,min/max}$	Maximum/minimum reactive power injected to the distribution network from upstream grid in time interval
39		t .
40	$Q_{i,max/min}^W$	Maximum/minimum reactive power generation of wind turbine in node i .
41	$\gamma_i^{max/min}$	Maximum/minimum limit (flexibility) of DR in node i .
42	α_i	Maximum percentage of allowed wind energy curtailment at node i .
43	Y_{ij}/θ_{ij}	Magnitude/angle of ij^{th} element of admittance matrix.
44	$(P/Q)_{t,i}^{D0}$	Original (no DR) active/reactive power in node i for time interval t .
45	$\cos(\phi_{i,t})$	Power factor limit of the wind turbine located node i in time period t .
46	D	Load level (as a percentage of peak load).

47 C. Variables

48	$Loss_t$	Active power losses in time t .
49	$(P/Q)_{i,t}^W$	Active/reactive power generation of wind turbine in node i for time interval t (MWh).
50	$P_{i,t}^D$	Active/reactive power demand in node i in the presence of DR for time interval t .
51	$P_{sb,t}/Q_{sb,t}$	Active/reactive power injected to the distribution network from upstream grid in time interval t .
52	$P_{i,t}^C$	Curtailed active power in node i for time interval t .
53	$I_{\ell,t}$	Current magnitude of line ℓ for time interval t .
54	$\gamma_{i,t}$	DR in node i for time interval t .
55	$(P/Q)_{i,t}^{net}$	Net active/reactive power injection to node i for time interval t .
56	$V_{i,t}/\delta_{i,t}$	Voltage magnitude/angle of node i for time interval t .
57	CP_i^W	Wind turbine capacity installed in node i .

II. INTRODUCTION

A. Background and Aims

The capacity of a distribution network for acceptance of new distributed generation (DG) units is called “hosting capacity” (HC). Calculation of the HC is an effective tool for determination of the most suitable locations for installation of DGs and hence, the investments will be guided toward the critical and most effective nodes of the grid. The distribution network operator/owner (DNO) is willing to increase this capacity since it would increase its benefits accrued due to connection fees. The presence of DG units has potential positive and negative aspects for DNO. The positive side of DG units include postponing the need for network reinforcement, reducing environmental pollutions, active power loss reduction, network restorations [1] and voltage profile improvement. These potential benefits would become actual if the DG units as well as the distribution network are operated and planned optimally. But, there are some barriers which may hinder this transition. Those are namely as follows:

- The intermittent renewable power generation: the main problem with renewable power generation resources is the volatility of their output [2] which is a function of different environmental parameters like temperature, solar radiation, wind speed [3] and etc. The only available option for controlling the wind power resources is its reactive power control or curtailment of its active power generation.
- Different objective functions of DNO and DG owners: the DNO and DG owner/operator (DGO) do not have the same objective functions (or strategies). This would result in conflict of interests or a financial gain or loss. One simple explanation is that DNO is interested to attract more wind power generation capacity in its territory (the same as DGO). This is because the DGO can sell more energy and DNO can receive more connection fees. However this may increase the active energy losses which is not desirable for DNO.

The smart grid technology provides more flexibility for DNO to optimize its goals. One of these powerful flexibilities is called the Demand Response (DR). The DR describes an interaction and responsiveness of the consumers and offers different potential benefits in operating and planning of power systems [4].

This paper, models the concerns of both DNO and DGO, by considering a multi-objective framework. Thus, focus of this work is to maximize the HC in distribution networks, as well as to minimize the energy losses. A mid-term perspective (one year) is considered which explores how a distribution network as well as the wind turbines should be operated in order to attract more wind power generation capacity without deteriorating the network efficiency (i.e. without increasing the total energy losses). The DR in form of flexible (shift-able) demand is utilized along with other control options such as wind power generation curtailment and/or reactive power outputs of wind turbines. *Any node which has non-zero demand can be used as the demand response node. No specific requirement is considered for the nodes to serve as demand response flexibility provider [5]. A technique for optimal DR node selection is provided in [6].*

B. Literature Review

There are some factors which limit the HC including: voltage step limits, thermal loading limits of feeders and voltage limits. The previous works in this area can be generally categorized into two groups: the first group tries to identify the HC of a given network while the second group tries to maximize it. In [7], a hybrid GA-OPF is proposed to identify the best size and location for a predetermined number of thermal DG units. It is assumed that all DG units operate at constant power factor. This model uses a single snapshot of demand in different nodes of the network. To consider the intrinsic variability of electric demand, a probabilistic load flow using Monte Carlo technique was proposed in [8] that analyzes the role of power factor capabilities of PV systems on increasing the HC in distribution networks. The impact of harmonic distortions on limiting the HC is analyzed in [9]. The available models proposed for maximizing the HC use different techniques to do so such as energy storage units [10], network reconfiguration [11], OLTC and SVC control [12], curtailment of renewable energy resources [13], cost-benefit analysis [14], active/reactive power control of PV inverter [15], active network management [16] and grid reinforcement. Most of the researches are based on the optimal power flow (OPF) models. These approaches are proposed to determine the available HC for DGs [17] and wind power [18] in a distribution networks. Genetic algorithm (GA) [19], and hybrid OPF and GA [7] are utilized to determine the optimal position and size of DGs. In [20], multi-period OPF is used to determine the maximum wind energy HC of distribution networks. Moreover active management strategies such as wind power curtailment [18], [20], reactive power compensation, voltage control using coordinated on-load tap changer [18], [20], and power factor (PF) control of wind turbines [20] are investigated to increase the DG or wind power HC of distribution networks. In [17] authors proposed a methodology for determination of maximum DG capacity in radial low-voltage feeders. The methodology indicates the highest capacity that can be installed at a fixed point in the feeder for which the voltage is kept within the permissible limits in critical scenarios, especially in low load- high wind scenarios. In [18] a decentralized voltage control approach aimed to allow DG active power production maximization and to avoid DG disconnection due to voltage limit violation as much as possible. A local active/reactive power management control strategy was proposed based on Artificial Neural Networks, able to regulate voltage profiles at buses where DGs are connected, taking into account their capability curve constraints. In [19] probabilistic approaches were proposed to in order to determine maximum DG penetration in medium voltage distribution networks. In [20] curtailment is used to allow more wind or solar power to be connected to a distribution network when over-current or over-voltage occurs. In this regard, the concepts of “hard curtailment” and “soft curtailment” were introduced. A model based on cost benefit analysis is proposed in [14] for determining the optimal wind power HC of a distribution system using active-management strategies (AMSs). In [21] the economical benefits of different autonomous inverter control strategies for increasing the HC of a real low voltage grid in Germany. The costs of these strategies are compared with those of two alternative approaches, traditional

grid reinforcement and a distribution transformer with OLTC. In [22], a probabilistic methodology is presented which integrates DR in real-time distribution energy market. The model proposed in [22], is day ahead and a single objective approach.

C. Contributions

To the best of our knowledge, no work in the literature considers DR to increase the HC of distribution networks as well as minimizing the total energy losses. Accordingly, the contributions of current research are as follows:

- 1) To investigate the impact of demand flexibility (in the context of DR program) on the maximization of wind power HC and minimization of energy losses in power distribution systems.
- 2) The proposed model considers the contradicting objectives of DNO and DGO simultaneously.
- 3) A multi-period AC power flow model is proposed to capture the variation of wind power and demand levels. All technical network constraints such as thermal rating of feeders and voltage limits have been considered, which makes the proposed model practical and realistic.

In this work, the demand level as well as wind power generations in different sites are assumed to be known. However these values are subject to uncertainty. There are several methods for handling the uncertainties existing in the defined problem such as stochastic methods [23], robust optimization [24] and Information gap decision theory [25].

D. Paper Organization

The remainder of the paper is organized as follows. Section III describes the problem formulation and presents the modeling features and assumptions made in the proposed decision making framework. Simulation results and discussions are presented in Section IV. Section V concludes the paper.

III. PROBLEM FORMULATION

A. Assumptions

- The proposed model is run on a yearly basis (i.e. 56 periods with different durations are considered).
- The DNO has the authority for controlling demands in some specific nodes (in the context of DR program). This can happen using mutual agreement/contract between the consumers and the DNO [26]. The gained benefits of this agreement will be shared between the DNO and the consumers.
- The main idea of the proposed framework is to demonstrate and quantify the effectiveness of the developed model for determination of the HC. The model receives some inputs and provides some insights regarding the HC as well as the energy losses as shown in Fig. 1. The trade-off curve between the HC and energy losses is determined.

159 B. Constraints

The objective functions to be optimized are defined as follows:

$$OF_1 = \sum_i CP_i^W \quad i \in \Omega_W \quad (1)$$

$$OF_2 = \sum_t Loss_t \tau_t \quad t \in \Omega_T \quad (2)$$

In (1), the installed capacity of wind turbines (in node i (CP_i^W)) are summed over all candidate nodes to represent the HC ($OF_1 = HC$). In (2), the total energy losses (OF_2) are calculated by summation of active power loss in time t ($Loss_t$) multiplied by the duration of period t (τ_t).

The power flow equations to be satisfied $\forall i \in \Omega_n, \forall t \in \Omega_T, \forall \ell \in \Omega_L$ are as follows:

$$Loss_t = \sum_i P_{i,t}^{net} \quad (3)$$

$$P_{i,t}^{net} = V_{i,t} \sum_{j \in \Omega_n} Y_{ij} V_{j,t} \cos(\delta_{i,t} - \delta_{j,t} - \theta_{ij}) \quad (4)$$

$$Q_{i,t}^{net} = V_{i,t} \sum_{j \in \Omega_n} Y_{ij} V_{j,t} \sin(\delta_{i,t} - \delta_{j,t} - \theta_{ij}) \quad (5)$$

$$V_{min} \leq V_{i,t} \leq V_{max} \quad (6)$$

$$I_{\ell,t} = |Y_{\ell=ij} \angle \theta_{ij} (V_{i,t} \angle \delta_{i,t} - V_{j,t} \angle \delta_{j,t})| \leq \bar{I}_{\ell} \quad (7)$$

The following equations hold for demand nodes $\forall i \in \Omega_D, \forall t \in \Omega_T$, as follows:

$$P_{i,t}^{net} = -P_{i,t}^D \quad (8)$$

$$Q_{i,t}^{net} = -Q_{i,t}^D \quad (9)$$

The following equations hold for wind connection candidate nodes $\forall i \in \Omega_W, \forall t \in \Omega_T$, as follows:

$$P_{i,t}^{net} = P_{i,t}^W - P_{i,t}^D - P_{i,t}^C \quad (10)$$

$$Q_{i,t}^{net} = Q_{i,t}^W - Q_{i,t}^D \quad (11)$$

$$P_{i,t}^W = \varsigma_{i,t}^w CP_i^W \quad (12)$$

$$Q_{i,min}^W \leq Q_{i,t}^W \leq Q_{i,max}^W \quad (13)$$

$$-tg(\phi_{i,t})P_{i,t}^W \leq Q_{i,t}^W \leq tg(\phi_{i,t})P_{i,t}^W \quad (14)$$

$$P_{i,t}^C \leq P_{i,t}^W \quad (15)$$

$$\sum_t P_{i,t}^C \tau_t \leq \alpha_i \sum_t P_{i,t}^W \tau_t \quad (16)$$

where $P_{i,t}^{net}, Q_{i,t}^{net}$ in (10) and (11) are the net injected active and reactive power to bus i , respectively. $P_{i,t}^C$ in (10) is the wind power curtailed in bus i and time t . Equations (13) to (14) describe the capability curve of wind turbines. The maximum allowed curtail-able power is limited by the available wind generation in bus i and time t as given in (15). Additionally, the total curtail-able energy is limited by a predefined fraction (α_i) of all generated energy at node i as given in (16). Y_{ij}, θ_{ij} are the magnitude and angle of the admittance connecting bus i to j , respectively. $V_{i,t}, V_{min}, V_{max}$ in (6) are the voltage magnitude, min/max operating limits of each bus, respectively. I_ℓ in (7) is the current passing through feeder ℓ and $\bar{I}_\ell$ in (7) is the maximum allowable current in feeder ℓ . $P_{i,t}^W, Q_{i,t}^W$ in (10) and (11) are the active and reactive power injected to the network by the DG units or grid connection. $\Omega_n, \Omega_T, \Omega_L$ are the set of system nodes, operating hours, feeders, respectively.

Also, in the slack bus (i.e. the bus which connects the distribution network to the upstream grid), the following constraints are hold ($\forall i \in \Omega_{sb}, \forall t \in \Omega_T$):

$$P_{i=sb,t}^{net} = P_{sb,t} - P_{i=sb,t}^D \quad (17)$$

$$Q_{i=sb,t}^{net} = Q_{sb,t} - Q_{i=sb,t}^D \quad (18)$$

$$P_{sb,min} \leq P_{sb,t} \leq P_{sb,max} \quad (19)$$

$$Q_{sb,min} \leq Q_{sb,t} \leq Q_{sb,max} \quad (20)$$

DR constraints for $\forall i \in \Omega_{DR}, \forall t \in \Omega_T$ are as follows.

$$P_{i,t}^D = P_{i,t}^{D0} \times \gamma_{i,t} \quad (21)$$

$$Q_{i,t}^D = Q_{i,t}^{D0} \times \gamma_{i,t} \quad (22)$$

$$\gamma_{i,t} \leq (1 + \gamma_i^{max} \lambda_i) \quad (23)$$

$$\gamma_{i,t} \geq (1 - \gamma_i^{min} \lambda_i) \quad (24)$$

$$\sum_{t \in \Omega_T} \tau_t \times P_{i,t}^D = \sum_{t \in \Omega_T} \tau_t \times P_{i,t}^{D0} \quad (25)$$

$$\sum_{t \in \Omega_T} \tau_t \times Q_{i,t}^D = \sum_{t \in \Omega_T} \tau_t \times Q_{i,t}^{D0} \quad (26)$$

The set of demands participating in DR program is represented by Ω_{DR} . $P_{i,t}^{D0}, Q_{i,t}^{D0}$ specify the original demand pattern without DR perturbation in (21), (22). $\gamma_{i,t}$ denotes the decision variable for changing the demand pattern in (21),(22). The constraints (23),(24) model the flexibility degree of the demands. γ_i^{max} and γ_i^{min} specify the maximum possible increase and decrease of demand in each hour. Also, λ_i is a binary parameter. If $\lambda_i = 0$ then the node i does not participate in a DR program and vice versa. Although the demand pattern changes, the total energy consumption of the demands remain constant as

imposed by (25) and (26).

IV. CASE STUDY AND SIMULATION RESULTS

A. Data

The proposed algorithm is implemented in GAMS [27] environment and solved by SNOPT solver [28], running on an Intel®Xeon™CPU E5-1620 3.6 GHz PC with 8 GB RAM. It is applied to a 69-bus distribution network [29]. The proposed framework considers one year as the planning horizon. The total number of hours in each year are 8760 hours. In order to reduce the computation burden, these 8760 hours have been categorized into 56 clusters as given in Table I [11]. The duration of each cluster as well as the demand and wind generation are assumed to be known.

TABLE I
WIND-LOAD DURATION AND VARIATION PATTERN

Period	D (pu)	$\varsigma_{i,t}^{w1}$ (pu)	$\varsigma_{i,t}^{w2}$ (pu)	τ_t (h)	Period	D (pu)	$\varsigma_{i,t}^{w1}$ (pu)	$\varsigma_{i,t}^{w2}$ (pu)	τ_t (h)
t_1	0.3	0	0	1	t_{29}	0.7	0.1	0.3	362
t_2	0.3	0	0.1	9	t_{30}	0.7	0.3	0.3	310
t_3	0.3	0.1	0.1	50	t_{31}	0.7	0.3	0.5	429
t_4	0.3	0.1	0.3	13	t_{32}	0.7	0.5	0.5	168
t_5	0.3	0.3	0.3	7	t_{33}	0.7	0.5	0.7	334
t_6	0.4	0.3	0.5	20	t_{34}	0.7	0.7	0.7	127
t_7	0.4	0.5	0.5	5	t_{35}	0.8	0.7	0.9	377
t_8	0.4	0.5	0.7	2	t_{36}	0.8	0.9	0	14
t_9	0.3	0.7	0.7	1	t_{37}	0.8	0.9	0.9	668
t_{10}	0.3	0.9	0.9	2	t_{38}	0.8	0.9	1	274
t_{11}	0.5	0	0	148	t_{39}	0.8	1	0.9	185
t_{12}	0.5	0	0.1	113	t_{40}	0.8	1	1	45
t_{13}	0.5	0.1	0.1	875	t_{41}	0.8	0	0	41
t_{14}	0.5	0.1	0.3	241	t_{42}	0.9	0	0.1	14
t_{15}	0.5	0.3	0.3	255	t_{43}	0.9	0.1	0.1	195
t_{16}	0.5	0.3	0.5	342	t_{44}	0.9	0.1	0.3	60
t_{17}	0.5	0.5	0.5	118	t_{45}	0.9	0.3	0.3	35
t_{18}	0.5	0.5	0.7	282	t_{46}	0.9	0.3	0.5	60
t_{19}	0.5	0.7	0.7	81	t_{47}	0.9	0.5	0.5	23
t_{20}	0.6	0.7	0.9	262	t_{48}	0.9	0.5	0.7	62
t_{21}	0.6	0.9	0	8	t_{49}	0.9	0.7	0.7	11
t_{22}	0.6	0.9	0.9	329	t_{50}	0.9	0.7	0.9	76
t_{23}	0.6	0.9	1	118	t_{51}	0.9	0.9	0	11
t_{24}	0.6	1	0.9	51	t_{52}	0.9	0.9	0.9	123
t_{25}	0.6	1	1	12	t_{53}	0.9	0.9	1	40
t_{26}	0.7	0	0	192	t_{54}	0.9	1	0.9	43
t_{27}	0.7	0	0.1	127	t_{55}	0.9	1	1	5
t_{28}	0.7	0.1	0.1	1003	t_{56}	1	0.3	0.5	1

The power factor limit of each wind turbine is assumed to be $\cos(\phi_{i,t}) = 0.95$ (lag/lead). The maximum percentage of allowed wind energy curtailment (α_i) in (16) is assumed to be 10% ($\forall i \in \Omega_W$). It is assumed that candidate connection points are known as depicted in Fig. 2. The candidate wind connection nodes (Ω_W) are as follows: wind sites in nodes 4, 13, 17 and 29 follow the wind pattern 1 ($\varsigma_{i,t}^{w1}$), while the wind sites in nodes 32, 38, 46 and 55 follow the wind pattern 2 ($\varsigma_{i,t}^{w2}$) as described in Table I. It is also assumed that all nodes can participate in DR program ($\lambda_i = 1, \forall i \in \Omega_n$). The demand flexibility ($\gamma_i^{max/min}$) is assumed to be the same for all nodes and equal to 20%. The following three cases are studied in this section which are as follows:

- (Case-I) : Minimization of total energy losses

- (Case-II) : Maximization of HC
- (Case-III) : Trade off study between the above objectives

B. Case-I: Minimization of total energy losses

In this strategy, it is tried to determine the optimal capacity of wind turbines in distribution network (at the candidate nodes) in order to minimize total energy losses in the entire horizon of study. In order to solve the energy loss minimization problem, the following optimization problem is solved:

$$\min_{DV} OF_2 \quad (27)$$

Subject to :

(3) to (26)

The decision variables (DV) consist of control ($\bar{U}$) and dependent variables ($\bar{Y}$) which are defined as follows, respectively:

$$DV = \bar{U} \cup \bar{Y} \quad (28)$$

$$\bar{U} = \begin{bmatrix} V_{i,t} & \forall t \in \Omega_T, \forall i \in \Omega_n \\ \delta_{i,t} & \forall t \in \Omega_T, \forall i \in \Omega_n \\ P_{i,t}^C & \forall t \in \Omega_T, \forall i \in \Omega_W \\ Q_{i,t}^W & \forall t \in \Omega_T, \forall i \in \Omega_W \\ CP_i^W & \forall i \in \Omega_W \\ \gamma_{i,t} & \forall t \in \Omega_T, \forall i \in \Omega_{DR} \end{bmatrix} \quad (29)$$

$$\bar{Y} = \begin{bmatrix} Loss_t & \forall t \in \Omega_T \\ P_{i,t}^{net} & \forall t \in \Omega_T, \forall i \in \Omega_n \\ Q_{i,t}^{net} & \forall t \in \Omega_T, \forall i \in \Omega_n \\ I_{\ell,t} & \forall t \in \Omega_T, \forall \ell \in \Omega_L \end{bmatrix} \quad (30)$$

The optimal installed capacity of wind turbines in all candidate nodes are depicted in Fig. 3. The optimal total energy losses is obtained 2.55 MWh in this case. It is evidently observed from Fig. 3 that the wind capacities are allocated in all candidate nodes. The total HC is 5.34 MW in this case. Also, the node 55 is the maximum absorbing capacity (1.28 MW) whereas the node 13 is the minimum absorbing capacity (0.31 MW). It is assumed that all nodes can participate in DR program, however it can be controlled using the λ_i in node i as described in (23) and (24). If the node i is excluded from DR program, then the corresponding $\lambda_i = 0$. The average DR action (i.e. $\frac{\sum_i \gamma_{i,t}}{|\Omega_n|}$) vs time period is depicted in Fig. 4.

The reactive power control capability of wind turbines allows to change the reactive power flows in distribution feeders. Hence, they affect on the magnitudes of currents flowing through distribution feeders and consequently on the energy losses. The reactive power dispatch of wind turbines ($Q_{i,t}^W$) vs time period

are given in Fig. 5. It can be observed that all wind turbines are required to inject reactive power to the network, in order to supply the reactive power demands of neighbor nodes.

The active/reactive power supply by the upstream network vs time is shown in Fig. 6. In most periods the reactive power is supplied through the upstream network. However, in some periods no active power is supplied by the slack bus, and the network demand is procured through wind turbines, and the surplus reactive power is injected to the upstream system.

It is not desirable for DNOs to curtail the wind power generation. However in some periods due to technical constraints (such as power balance constraints, voltages and currents limits) the DNO is obliged to reduce the injected power of the wind turbines to the grid. This is likely occur in the light loading condition and highly available wind power generations circumstances. The curtailed power in each wind site ($P_{i,t}^C$) vs time is plotted in Fig. 7.

The total curtailed wind energy is obtained 2071.71 MWh in this case. This amount of curtailed energy is allocated between the installed wind turbines, non uniformly. The maximum share is 22.54% which corresponds to node 55 (467.10 MWh), whereas the minimum share is 6.27% corresponding to node 13 (129.98 MWh).

It would be interesting to know that what is the impact of demand flexibility on total energy loss minimization. For this aim, a sensitivity analysis is performed in which the demand flexibility ($\gamma_{i,t}$) is changed from 0 to 20% and variation of total energy losses as well as HC are obtained, which are depicted in Fig. 8. For ($\gamma_{i,t} = 0$), total energy losses and HC are 3.27 MWh and 4.46 MW, respectively. As the demand flexibility increases to 20% the former decreases while the latter capacity increases. The total energy losses and HC are 2.55 MWh and 5.33 MW, respectively for ($\gamma_{i,t} = 0.20$, or 20%).

C. Case-II: HC maximization

In order to maximize HC the following optimization problem is solved:

$$\max_{DV} OF_1 \tag{31}$$

Subject to :

(3) to (26)

In this case, by solving the above optimization problem, only in the nodes 29, 38 and 55 wind turbines are installed, and no wind power generation is allocated in the remaining nodes. The optimal installed capacity of wind turbines in the aforementioned nodes are depicted in Fig. 9. The total allocated wind power generation capacity is 6.58 MW in this case, and wind capacities in nodes 29, 38 and 55 are 0.15 MW, 0.75 MW and 5.68 MW, respectively.

The DR is also scheduled for each node individually. It is a both time and node dependent action ($\gamma_{i,t}$). Hence, the average DR action for all nodes vs time period is given in Fig. 10.

The reactive power outputs of wind turbines vs time period ($Q_{i,t}^W$) are depicted in Fig. 11. In some periods (i.e. light loads) the wind turbines absorb reactive power, whereas in some periods (i.e. in high load levels) they inject reactive power to the network.

The active/reactive power supply by the upstream network vs time is depicted in Fig. 12. It is observed from this figure that in most periods the reactive power is supplied by the upstream network and only in two periods it is absorbed by the upstream network. As it is observed from Fig. 11, in these periods considerable reactive power is generated by all wind turbines and hence the excessive reactive power is injected to the upstream network via slack bus. However, in some periods no active power is supplied by the slack bus.

In HC maximization strategy, the curtailed wind power in each wind site (i.e. $P_{i,t}^C$) vs time period is shown in Fig. 13. This figure indicates that the total curtailed energy is 2403.47 MWh. The share of wind energy curtailment in node 29 is 2.59%, in node 38 is 11.36 % and the rest (86.04%) is curtailed in node 55.

Also a sensitivity analysis is carried out to investigate the impact of demand flexibility on HC and total energy losses. Variation of these objectives versus demand flexibility is depicted in Fig. 14. By increasing the demand flexibility ($\gamma_i^{max/min}$) from 0 to 20%, the HC increases from 5.57 MW to 6.58 MW. But, contrary to Case-I, total energy losses increases from 23.04 MWh to 39.01 MWh in this case as a result of improvement of HC.

D. Case-III: Trade off analysis

In order to perform a trade-off analysis between the HC maximization and total energy loss minimization ϵ -constraint method [30] is used in this paper. The following optimization problem is solved for various values of ϵ . For this purpose, the ϵ is decreased from OF_2^{max} to OF_2^{min} gradually and the maximum value of OF_1 is sought by finding the optimal values of decision variables DV . OF_2^{min} is the solution of (27) when the strategy is minimizing the total energy losses (i.e. the solution obtained in Case-I). Also, OF_2^{max} is the value of total energy losses when (31) is solved (the strategy is maximizing the HC).

$$\max_{DV} OF_1 \quad (32)$$

Subject to :

$$OF_2 \leq \epsilon \quad (33)$$

(3) to (26)

The Pareto optimal front which shows the variation of total energy losses reduction vs HC maximization is shown in Fig. 15. It is evidently observed from this figure that by increasing the HC, total energy

reduction is decreased which shows conflict of these considered two objectives. For different values of these objectives, the value of installed wind turbines varies (as it is seen in Case-I and Case-II). Figure 16 depicts the variation of installed wind power generation capacities at all candidate nodes vs the HC. It is observed from this figure that beyond the amount of 6.20 MW, unless the nodes 29, 38 and 55, the installed wind turbine capacity in all remaining node vanishes.

There are different ways of selecting the final solution from the Pareto optimal set. Fuzzy satisfying method [31] is one of the well known techniques used for achieving a trade-off between different objective functions. In this approach, at each Pareto optimal solution a fuzzy number is assigned for each objective function, which maps it to the interval [0, 1]. This normalized Fuzzy number is a good measure to compare the quality of Pareto optimal solutions. For the entire Pareto optimal set, the number of best compromise solution is obtained by using min-max criterion. Also, the selected candidate nodes for wind turbine connection in different ranges of HC are described in Table II. This table indicates that by increasing the HC, wind power generation is concentrated on some limited nodes which are the nodes 29, 38 and 55 in this system. But this concentration increases the total energy losses, because a high amount of active/reactive power is injected by wind turbines in these nodes. Contrarily, in the lower levels of HC (which corresponds to lower levels of total energy losses), the wind hosting nodes are outspread around the entire system. This leads to lower energy losses, because the hosted wind energy is injected from various locations and hence the current amplitudes in the branches will be lower.

TABLE II
THE SELECTED CANDIDATE NODES FOR WIND TURBINE CONNECTION IN DIFFERENT RANGES OF HC

HC variation range (MW)		Candidate connection node (<i>i</i>)							
HC_{min}	HC_{max}	4	13	17	29	32	38	46	55
6.2205	6.5817				✓		✓		✓
6.0213	6.2081				✓		✓	✓	✓
5.9964	6.0088		✓		✓		✓	✓	✓
5.4609	5.9839		✓		✓	✓	✓	✓	✓
5.4111	5.4484	✓	✓		✓	✓	✓	✓	✓
5.3383	5.3986	✓	✓	✓	✓	✓	✓	✓	✓

V. CONCLUSIONS

In this paper, a multi-objective DR framework is presented in which the loss minimization as well as the HC maximization are analyzed. The simulation results show that the proposed strategy can be used by DNOs in practical cases. As evidenced by the simulation results, the proposed method offers some interesting features over traditional methods as follows:

- It models the variation patterns of demand and wind power generation.
- It can be utilized to assess the merits of nodes for participating in DR programs based on their contributions to HC maximization as well as the active energy loss minimization. The only change

which is necessary to be made to the current formulation is changing the parameter (λ_i) in ((23) to (24)) into a binary variable and add it to the (28). The new model would become a mixed integer non-linear programming (MINLP) model.

- The flexibility and generality of the proposed method makes it suitable for considering other active management strategies such as network reconfiguration [32], capacitor switching, energy storage units and etc.
- The results provided by proposed model can be used to provide incentive signals for DGOs. In this way a percentage of the DNO's benefits (due to loss reduction) can be paid to DGOs in order to guide their decisions toward what it is desired by DNO. These incentives can be reflected in connection fees as well.
- The scope of this work is limited to DR and reactive power control of wind turbines to increase the HC of distribution networks. Any kind of flexibility existing in distribution network can be helpful to improve the quality of the obtained solutions. These flexibilities can be capacitor banks' switching, network reconfiguration, network reinforcement, OLTC tap ratio control, energy storage devices utilization and etc.

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Fig. 12. The active/reactive power supply by the upstream network vs time- (Case-II)

Fig. 13. The curtailed power in each wind site vs time $P_{i,t}^C$ (MW)- (Case-II)

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Fig. 16. The variation of installed capacity at the candidate nodes vs the HC

REFERENCES

- [1] B. Ansari, M. G. Simoes, A. Soroudi, and A. Keane, "Restoration strategy in a self-healing distribution network with dg and flexible loads," in *2016 IEEE 16th International Conference on Environment and Electrical Engineering (EEEIC)*, June 2016, pp. 1–5.
- [2] S. Shargh, B. K. ghazani, B. Mohammadi-ivatloo, H. Seyedi, and M. Abapour, "Probabilistic multi-objective optimal power flow considering correlated wind power and load uncertainties," *Renewable Energy*, vol. 94, pp. 10 – 21, 2016.
- [3] E. M. Gouveia and M. A. Matos, "Evaluating operational risk in a power system with a large amount of wind power," *Electric Power Systems Research*, vol. 79, no. 5, pp. 734 – 739, 2009.
- [4] P. Siano, "Demand response and smart gridsa survey," *Renewable and Sustainable Energy Reviews*, vol. 30, no. 0, pp. 461 – 478, 2014.
- [5] A. Soroudi, A. Rabiee, and A. Keane, "Distribution network hosting capacity maximization using demand response," *CIRE2015, June15G18*, 2015.
- [6] C. Murphy, A. Soroudi, and A. Keane, "Information gap decision theory-based congestion and voltage management in the presence of uncertain wind power," *IEEE Transactions on Sustainable Energy*, vol. 7, no. 2, pp. 841–849, April 2016.
- [7] G. P. Harrison, A. Piccolo, P. Siano, and A. R. Wallace, "Hybrid ga and opf evaluation of network capacity for distributed generation connections," *Electric Power Systems Research*, vol. 78, no. 3, pp. 392 – 398, 2008.
- [8] A. Ballanti, F. Pilo, A. Navarro-Espinosa, and L. F. Ochoa, "Assessing the benefits of pv var absorption on the hosting capacity of lv feeders," in *IEEE PES ISGT Europe 2013*, Oct 2013, pp. 1–5.
- [9] I. Nunes Santos, M. Bollen, and P. Ribeiro, "Methodology for estimation of harmonic hosting," in *Harmonics and Quality of Power (ICHQP), 2014 IEEE 16th International Conference on*, May 2014, pp. 708–712.
- [10] N. Etherden and M. Bollen, "Dimensioning of energy storage for increased integration of wind power," *Sustainable Energy, IEEE Transactions on*, vol. 4, no. 3, pp. 546–553, July 2013.
- [11] F. Capitanescu, L. Ochoa, H. Margossian, and N. Hatziaargyriou, "Assessing the potential of network reconfiguration to improve distributed generation hosting capacity in active distribution systems," *Power Systems, IEEE Transactions on*, vol. 30, no. 1, pp. 346–356, Jan 2015.
- [12] S. Wang, S. Chen, L. Ge, and L. Wu, "Distributed generation hosting capacity evaluation for distribution systems considering the robust optimal operation of oltc and svc," *IEEE Transactions on Sustainable Energy*, vol. 7, no. 3, pp. 1111–1123, July 2016.
- [13] N. Etherden and M. Bollen, "Increasing the hosting capacity of distribution networks by curtailment of renewable energy resources," in *PowerTech, 2011 IEEE Trondheim*, June 2011, pp. 1–7.
- [14] S. N. Salih, P. Chen, O. Carlson, and L. B. Tjernberg, "Optimizing wind power hosting capacity of distribution systems using cost benefit analysis," *IEEE Transactions on Power Delivery*, vol. 29, no. 3, pp. 1436–1445, June 2014.
- [15] L. Collins and J. Ward, "Real and reactive power control of distributed {PV} inverters for overvoltage prevention and increased renewable generation hosting capacity," *Renewable Energy*, vol. 81, pp. 464 – 471, 2015.
- [16] S. Abapour, K. Zare, and B. Mohammadi-Ivatloo, "Maximizing penetration level of distributed generations in active distribution networks," in *Smart Grid Conference (SGC), 2013. IEEE*, 2013, pp. 113–118.
- [17] I. T. Papaioannou and A. Purvins, "A methodology to calculate maximum generation capacity in low voltage distribution feeders," *International Journal of Electrical Power & Energy Systems*, vol. 57, pp. 141–147, 2014.
- [18] P. Siano, P. Chen, Z. Chen, and A. Piccolo, "Evaluating maximum wind energy exploitation in active distribution networks," *IET Generation, Transmission Distribution*, vol. 4, no. 5, pp. 598–608, May 2010.
- [19] M. Kolenc, I. Papič, and B. Blažič, "Assessment of maximum distributed generation penetration levels in low voltage networks using a probabilistic approach," *International Journal of Electrical Power & Energy Systems*, vol. 64, pp. 505–515, 2015.
- [20] N. Etherden and M. H. Bollen, "Overload and overvoltage in low-voltage and medium-voltage networks due to renewable energy–some illustrative case studies," *Electric Power Systems Research*, vol. 114, pp. 39–48, 2014.
- [21] T. Stetz, F. Marten, and M. Braun, "Improved low voltage grid-integration of photovoltaic systems in germany," *Sustainable Energy, IEEE Transactions on*, vol. 4, no. 2, pp. 534–542, 2013.
- [22] P. Siano and D. Sarno, "Assessing the benefits of residential demand response in a real time distribution energy market," *Applied Energy*, vol. 161, pp. 533 – 551, 2016.

- [23] A. Soroudi and T. Amraee, "Decision making under uncertainty in energy systems: State of the art," *Renewable and Sustainable Energy Reviews*, vol. 28, pp. 376–384, 2013.
- [24] S. Nojavan, B. Mohammadi-Ivatloo, and K. Zare, "Robust optimization based price-taker retailer bidding strategy under pool market price uncertainty," *International Journal of Electrical Power & Energy Systems*, vol. 73, pp. 955–963, 2015.
- [25] M. Moradi-Dalvand, B. Mohammadi-Ivatloo, N. Amjady, H. Zareipour, and A. Mazhab-Jafari, "Self-scheduling of a wind producer based on information gap decision theory," *Energy*, vol. 81, pp. 588–600, 2015.
- [26] X. He, N. Keyaerts, I. Azevedo, L. Meeus, L. Hancher, and J.-M. Glachant, "How to engage consumers in demand response: A contract perspective," *Utilities Policy*, vol. 27, no. 0, pp. 108 – 122, 2013.
- [27] R. Rosenthal, *GAMS: a user's guide*. GAMS Development Corporation, 2012.
- [28] P. Gill, W. Murray, and M. Saunders, "Snopt: An sqp algorithm for large-scale constrained optimization," *SIAM journal on optimization*, vol. 12, no. 4, pp. 979–1006, 2002.
- [29] D. Das, "A fuzzy multiobjective approach for network reconfiguration of distribution systems," *Power Delivery, IEEE Transactions on*, vol. 21, no. 1, pp. 202–209, Jan 2006.
- [30] M. Laumanns, L. Thiele, and E. Zitzler, "An efficient, adaptive parameter variation scheme for metaheuristics based on the epsilon-constraint method," *European Journal of Operational Research*, vol. 169, no. 3, pp. 932–942, 2006.
- [31] A. Soroudi and M. Afrasiab, "Binary pso-based dynamic multi-objective model for distributed generation planning under uncertainty," *IET renewable power generation*, vol. 6, no. 2, pp. 67–78, 2012.
- [32] V. Calderaro, V. Lattarulo, A. Piccolo, and P. Siano, "Optimal switch placement by alliance algorithm for improving microgrids reliability," *Industrial Informatics, IEEE Transactions on*, vol. 8, no. 4, pp. 925–934, Nov 2012.