Link to original published version: http://dx.doi.org/ 10.1016/j.solener.2015.10.052

Citation: Mokryani G (2015) Active distribution networks planning with integration of demand response. Solar Energy. 122: 1362-1370.

Active Distribution Networks Planning with Integration of Demand Response

Geev Mokryani
School of Electrical Engineering and Computer Science, University of Bradford, Bradford BD7 1DP, UK
Email: g.mokryani@bradford.ac.uk

***Abstract* –This paper proposes a probabilistic method for active distribution networks planning with integration of demand response. Uncertainties related to solar irradiance, load demand and future load growth are modelled by probability density functions. The method simultaneously minimizes the total operational cost and total energy losses of the lines from the point of view of distribution network operators with integration of demand response over the planning horizon considering active management schemes including coordinated voltage control and adaptive power factor control. Monte Carlo simulation method is employed to use the generated probability density functions and the weighting factor method is used to solve the multi-objective optimization problem. The effectiveness of the proposed method is demonstrated with 16-bus UK generic distribution system.**

***Index Terms* — Photovoltaic cells, uncertainties, loss minimization, demand response, distribution network operators, Monte Carlo simulation.**

NOMENCLATURE

A. Indices

b	*Slack bus*
i,j	*Buses*
g	*Generator buses*
l	*Loads*
t	*Number of years*

B. Variables

$V_{i,t}$	Voltage at bus i and year t
$\delta_{i,t}$	Voltage angle at bus i and year t
$P_{g,t} / Q_{g,t}$	Active/reactive power of PVs at each bus and year t
$P_{b,t} / Q_{b,t}$	Active/reactive power at slack bus at each bus and year t
T_{ij}	Tap magnitude of OLTC
$\phi_{g,t}$	Power factor angle of PVs at each bus and year t
$P^{i}_{DR(l,t)} / Q^{i}_{DR(l,t)}$	Active/reactive power decrement in demand response program for load demand l at bus i and year t

C. Parameters

w_1, w_2	Weighting factors
G_{ij} / B_{ij}	Real/imaginary part of the element in the admittance matrix corresponding to i^{th} row and j^{th} column
$P_{l,t}^i / Q_{l,t}^i$	Active/reactive power of load demand l at bus i and year t
$C_{g,t}^i$	Price offered by PVs to increase/decrease active power at bus i and year t
$C_{DR(l,t)}^i$	Price offered by load demand l at bus i and year t to decrease its active power schedule in the context of demand response
$S^{\max}$	Maximum solar inverter rating
$V_i^{\min} / V_i^{\max}$	Minimum/maximum values of voltage at bus i
$\delta_i^{\min} / \delta_i^{\max}$	Minimum/maximum values of voltage angle at bus i
$P_{g,t}^{\min} / P_{g,t}^{\max}$	Minimum/maximum values of active power of PVs at each bus and year t
$Q_{g,t}^{\min} / Q_{g,t}^{\max}$	Minimum/maximum values of reactive power of PVs at each bus and year t
$P_b^{\min} / P_b^{\max}$	Minimum/maximum values of active power of slack bus
$Q_b^{\min} / Q_b^{\max}$	Minimum/maximum values of reactive power of PVs at slack bus
$\phi_g^{\min} / \phi_g^{\max}$	Minimum/maximum values of power factor angles
$T_{ij}^{\min} / T_{ij}^{\max}$	Lower/upper values of the tap magnitude of OLTC

I. Introduction

A. *Aim and Approach*

Distributed generators (DGs) and renewable energy sources (RES) are supposed to develop the design and operation of distribution networks, which are evolving towards smart grids (SGs). The SG is defined as a grid which is able to deliver electricity to consumers in a smart and controlled way [1]. In fact, the advantages of SGs are because of its ability to improve reliability performance and responsiveness of customers and to encourage customers and the utility provider to make better decisions. Therefore, demand response (DR), represents an integral part of SG [2]. The integration of DR needs communication systems and sensors, automated metering, intelligent devices and specialized processors. DR refers to programs implemented by utility companies to manage the energy consumption at the customer side of the meter [3]. Both utilities and customers can receive the advantages of DR programs that can assist electricity markets to operate in an effective way, thus reducing peak demand and spot price volatility [4]. This paper provides a probabilistic multi-objective methodology for assessing the amount of PV power that can be injected into the grid and the energy losses of the lines with integration of DR considering active network management (ANM) schemes such as coordinated voltage control (CVC) and adaptive power factor control (PFC). The method simultaneously minimizes the total operational cost and the total energy losses of the lines from the point of view of DNOs over the planning horizon considering network constraints and uncertainties. The uncertainties related to solar irradiance, load demand and future load growth are modelled by probability density functions (PDFs). The stochastic nature of solar irradiance is modelled by Beta PDF and other abovementioned uncertainties are modelled by Normal PDF. Monte Carlo simulation (MCS) method is utilized to use the generated PDFs and the weighting factor method is used to solve the multi-objective optimization problem.

B. Literature Review

Probabilistic approaches are utilized to handle various uncertainties in planning and operations of distribution network. In [5], the authors proposed a combined MCS and optimal power flow (OPF) to maximize the social welfare by integrating DR scheme considering different combinations of wind generation and load demand over a year. A stochastic formulation of load margin taking into account the uncertainties related to RES integration into the network is proposed in [6]. In [7], a probabilistic reliability criterion considering uncertainties related to component outage in the expansion planning is proposed. Moreover, the method minimizes the investment budget for constructing new transmission lines considering the uncertainties of the transmission system. In [8], the MCS is used to combine the correlated load demands and wind power generations by using the multivariate distribution to choose random variables. The authors in [9] proposed a stochastic programming approach for reactive power scheduling of a microgrid considering the uncertainty of wind power. In [10], the authors presented that fast/emergency reserve can be provided by responsive loads such as residential and small commercial air conditioners. The control of residential heaters and pumps has been applied for managing daily peak demands in [11].

C. Contributions

To the best of our knowledge, no probabilistic method for evaluating the impact of ANM schemes and DR on operational cost and energy losses has been reported in the literature. The method allows the assessment of the amount of energy generated by PVs and the energy losses that can be reduced considering uncertainties and network constraints. The proposed probabilistic method can assist DNOs in evaluating the impact of PV integration in active distribution networks in terms of technical and economic effects. The method can be used by DNOs to better allocate PVs at more advantageous locations in terms of consumers' benefits and cost reduction, network constraints and reliability. Conventional planning of distribution networks involving renewable energy sources integration have not considered the combination of ANM schemes and DR on the operation of distribution network [12-13].

The gap that this paper tries to fill is how the combination of DR and ANM schemes can impact on the energy generated by PVs, total operational cost and network losses. Also, it investigates how it should be done considering uncertainties and DR. Therefore, the major contributions of this paper are highlighted as follows:

1) Proposing a MCS-based multi-objective optimization approach which takes into account DR and ANM schemes at the planning stage which has not been addressed so far.
2) Modelling the uncertainties related to solar irradiance, load demand and future load growth by PDFs.
3) Simultaneously minimizing total operational cost related to PV generation and load demand reduction and total active power losses of the lines.

D. Paper Organization

The rest of the paper is organized as follows. Section II explains the structure of the proposed method. The ANM schemes and uncertainty modeling are discussed in Sections III and IV, respectively. Problem formulation is described in Section V. Section VI presents the 16-bus UK generic distribution system (UKGDS) and simulation results. Discussion and conclusions are presented in Section VII.

II. THE STRUCTURE OF THE PROPOSED METHOD

The proposed probabilistic method is based on MCS considering stochastic variations of solar irradiance, load demand and future load growth over the planning horizon. The method randomly generates solar irradiance, load demand and load growth from probability density functions (PDFs). For each combination of solar irradiance and load demand, different multi-objective optimizations are carried out to simultaneously minimize the total operational cost and total energy losses with integration of DR considering ANM schemes and network constraints. A quantitative probabilistic analysis of technical indicators such as total operational cost, energy generated by PVs and energy losses can be achieved by the aggregate results of the MCS. The following steps are carried out by the proposed method. The following steps are carried out by the proposed method as shown in Fig.1.

1) Set the candidate buses according to solar irradiance historical data.
2) Define sizes of PVs and irradiance-power curves of PVs.
3) Model the uncertainty related to solar irradiance by using Beta PDF [14].
4) Derive the PDF of the PV's active power output on the basis of the Beta PDF of solar irradiance and irradiance to power conversion function of PVs as described in Section IV.
5) Model the uncertainties related to load demand and future load growth by Normal PDF [15].
6) Perform MCS of length N (number of samples).
7) For each sample of MCS, simultaneously minimize the total operational cost and total energy losses of the lines with integration of DR considering ANM schemes and network constraints. The formulation of multi-objective optimization problem is described in Section V.
8) The products of the proposed method provide the probabilistic energy generated by PVs, energy losses and total operational cost.

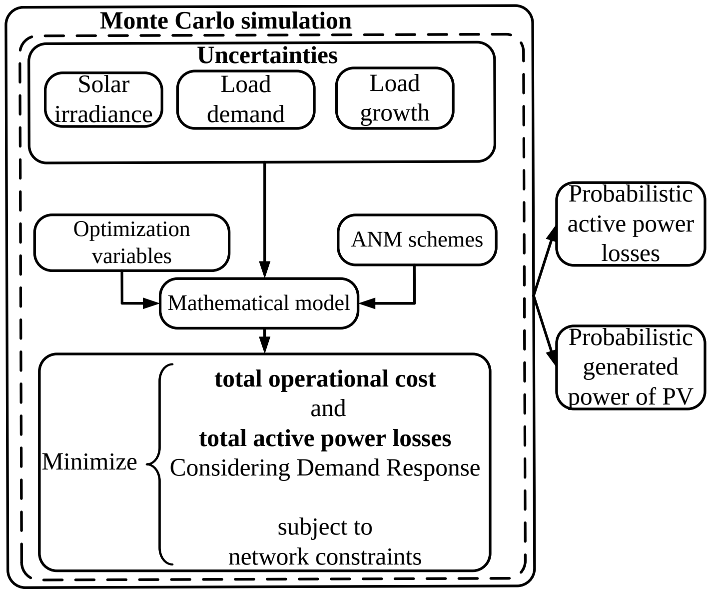


Fig.1.The structure of the proposed method

III. ANM SCHEMES

A. Coordinated Voltage Control

Conventional control approaches of on-load tap changer (OLTC) are either on the basis of voltage regulation at a single bus or the compensation of voltage drop on a specific line. This kind of control approaches are on the basis of local measurements and are appropriate for conventional distribution networks with unidirectional power flow. Nevertheless, these methods create problems in distribution networks with bi-directional power flows. Instead, the area-based control method of OLTCs is on the basis of measurements from network's numerous places. Thus, the OLTCs' voltage regulation can be on the basis of the voltage information of the bus that has the most severe overvoltage problem [16].

B. PV Reactive Power Control and Capability Curve

Conventional distribution systems determine constant values for the secondary voltages of substation and operate DGs, for different load conditions, at constant power factors whereas DNOs may differ the voltage of substation seasonally and determine power factor within a specified limit. Due to PV reactive power control, the power factors used by the PV differ according to the demand and generation levels. PV inverters have the capability of voltage support by controlling reactive power at the point of common coupling (PCC). The reactive power output and the voltage control capability of PV at the PCC are restricted by the apparent power rating of the inverter. Inverter overcapacity is required at maximum active power injection to give reactive power support [17] as shown in Fig.2.

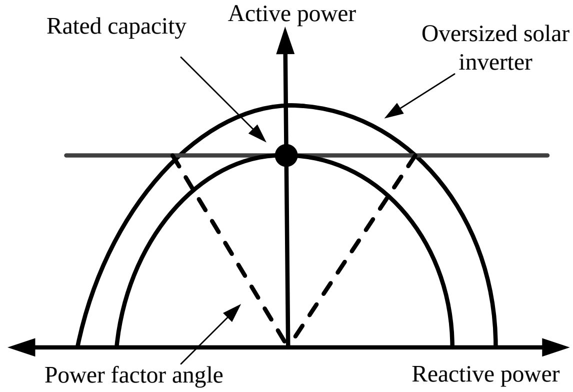


Fig.2. Capability curve of PV inverter

IV. Uncertainty Modeling

A. Output Power of Solar Generating Sources

The generated power of a PV module relies on three parameters, namely, solar irradiance, ambient temperature of the site and the characteristics of the module itself. The solar irradiance is modelled using a beta PDF [18] which is described as follows:

$$PDF(s) = \begin{cases} \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)+\Gamma(\beta)} \times s^{\alpha-1} \times (1-s)^{\beta-1}, & \text{if} \quad 0 \le s \le 1, 0 \le \alpha, \beta \\ 0, & \text{else} \end{cases} \quad (1)$$

where s represents the solar irradiance (kW/m^2). In order to calculate the parameters of Beta PDF (α, β), the mean (μ) and standard deviation (σ) of the random variable are utilized as follows:

$$\beta = (1-\mu) \times (\frac{\mu \times (1+\mu)}{\sigma^2} - 1) \quad (2a)$$

$$\alpha = \frac{\mu \times \beta}{1-\mu} \quad (2b)$$

The irradiance to power conversion function used in this paper is similar to that used in [19]:

$$P_{pv}(s) = \eta^{pv} \times S^{pv} \times s \quad (3)$$

where $P_{pv}(s)$ represents PV output power (kW) for irradiance s; η^{pv} and S^{pv} are the efficiency (%) and total area (m^2) of PV system, respectively. According to the given irradiance distribution and irradiance to power conversion function, the PV power distribution can be obtained.

B. Load Demand Uncertainty

The loads at each bus are modelled by a Normal PDF as follows:

$$PDF\,(S_i^L) = \frac{1}{\sqrt{(2\pi\sigma_i^L)}} \exp([\frac{(S_i^L - \mu_i^L)^2}{2(\sigma_i^L)^2}]) \qquad (4)$$

where S_i^L is the apparent power demand at bus i, μ_i^L and $(\sigma_i^L)^2$ are the mean and variance of demand at bus i, respectively.

C. *Future Load Growth*

Suppose that the original load l at bus i is $P_L^i(0)$, and the load growth at this bus in year t of the planning horizon is $\Delta P_L^i(t)$ and follows Normal PDF according to following formulation: $\Delta P_L^i(t) \sim N(\mu_i(t), \sigma_i^2(t))$. Thus, the load at bus i in year t is $P_L^i(t) = P_L^i(t-1) + \Delta P_L^i(t)$.

V. PROBLEM FORMULATION

In this paper, any branch is modeled as a symmetrical π series with an ideal transformer with ratio 1/T as shown in Fig.3.

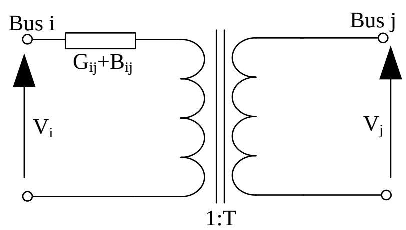


Fig.3. Model of a generic branch

A. *Objective Functions*

7% of electricity generated in the UK is lost as distribution losses but marginal losses are higher and may be up to 30% at the extreme edges of the networks [20]. Therefore, energy losses minimization has positive effects in distribution networks such as voltage drop reduction, voltage profile improvement and other economic and environmental advantages. On the other hand, from the point of view of DNOs, it is essential to evaluate the available distribution network capacity in terms of renewable DG penetration without needing extra investments in the network. However, the DR is an important resource that enables a more efficient system operation taking advantage of the active role that each consumer should assume in the system management in the scope of smart grid [21]. Therefore, based on these considerations, the objective of the proposed planning problem is jointly minimizing the total operational cost with integration of DR program and the total energy losses of the lines from the point of view of DNOs over the planning horizon considering ANM schemes subject to network constraints as described in the following.

Minimize $f_{obj} = w_1 f_{obj_1} + w_2 f_{obj_2}$

$$f_{obj_1} = \sum_{t=1}^{NT}\sum_{g=1}^{G} C_{g,t}^{i} \times P_{g,t}^{i} + \sum_{t=1}^{NT}\sum_{l=1}^{L} C_{DR(l,t)}^{i} \times P_{DR(l,t)}^{i} \quad (5)$$

$$f_{obj_2} = \sum_{t=1}^{NT}\sum_{i}\sum_{j} G_{ij}(V_{i,t}^2 + \frac{V_{j,t}^2}{T_{ij}^2} - 2\frac{V_{i,t}V_{j,t}\cos(\delta_{i,t}-\delta_{j,t})}{T_{ij}})$$

where f_{obj} is the total objective function. w_1, w_2 are weighting factors and $w_1 + w_2 = 1$. f_{obj_1} is the total operational cost. The first and second terms of f_{obj_1} are respectively the operational cost of the PVs and demand reduction. f_{obj_2} is the total energy losses of the lines over the planning horizon. $C_{g,t}^{i}$ is the price offered by each PV to increase/decrease active power at bus *i* and year *t*, $P_{g,t}^{i}$ is the generated active power by each PV at generator buses and year *t*. $P_{l,t}^{i} / Q_{l,t}^{i}$ is active/reactive power of load demand *l* at bus *i* and year *t*. $C_{DR(l,t)}^{i}$ is the price offered by load demand *l* at bus *i* and year *t* to decrease its active power schedule in the context of the DR program, $P_{DR(l,t)}^{i}$ is active power decrement in DR program for load demand *l* at bus *i* and year *t*. $V_{i,t}$, $\delta_{i,t}$ and $V_{j,t}$, $\delta_{j,t}$ are respectively voltage and voltage angle at buses *i* and *j* and year *t*. *NT* is the planning period.

B. Network Constraints

a) Equality Constraints: Active and reactive power balance at each bus and year

$$\sum_{g=1}^{G} P_{g,t}^{i} + \sum_{l=1}^{L}(P_{DR(l,t)}^{i} - P_{l,t}^{i}) = \sum_{j=1}^{N_{bus}} V_{i,t}V_{j,t}T_{ij}\left[G_{ij}\cos(\delta_{i,t}-\delta_{j,t}) + B_{ij}\sin(\delta_{i,t}-\delta_{j,t})\right] \quad (6a)$$

$$\sum_{g=1}^{G} Q_{g,t}^{i} + \sum_{l=1}^{L}(Q_{DR(l,t)}^{i} - Q_{l,t}^{i}) = \sum_{j=1}^{N_{bus}} V_{i,t}V_{j,t}T_{ij}\left[G_{ij}\sin(\delta_{i,t}-\delta_{j,t}) - B_{ij}\cos(\delta_{i,t}-\delta_{j,t})\right] \quad (6b)$$

where G_{ij} and B_{ij} are respectively the real and imaginary part of the element in the bus admittance matrix corresponding to the i^{th} row and j^{th} column, T_{ij} is the tap magnitude of OLTC, N_{bus} is the number of buses.

b) Inequality Constraints

-Branch flow constraints

$$\sqrt{(G_{ij}^2 + B_{ij}^2)(V_{i,t}^2 + \frac{V_{j,t}^2}{T_{ij}^2} - 2\frac{V_{i,t}V_{j,t}\cos(\delta_{i,t} - \delta_{j,t})}{T_{ij}})} \le I_{ij}^{\max} \qquad (7)$$

where $I_{ij}^{\max}$ is the maximum current flow of wires.

-Voltage limits at each bus

$$V_i^{\min} \le V_{i,t} \le V_i^{\max} \qquad (8)$$

$$\delta_i^{\min} \le \delta_{i,t} \le \delta_i^{\max} \qquad (9)$$

where $V_{i,t}$ and $\delta_{i,t}$ are respectively the voltage magnitude and voltage angle at bus i and year *t*, $V_i^{\min} / V_i^{\max}$ and $\delta_i^{\min} / \delta_i^{\max}$ represent the *min/max* values they can assume.

-PV generation constraint

$$P_{g,t}^{\min} \le P_{g,t} \le P_{g,t}^{\max} \qquad (10)$$

$$Q_{g,t}^{\min} \le Q_{g,t} \le Q_{g,t}^{\max} \qquad (11)$$

$$\sqrt{P_{g,t}^2 + Q_{g,t}^2} \le S^{\max} \qquad (12)$$

where $P_{g,t}$ and $Q_{g,t}$ are respectively generated active and reactive powers of PV at each bus at year *t*; $P_{g,t}^{\min} / P_{g,t}^{\max}$ and $Q_{g,t}^{\min} / Q_{g,t}^{\max}$ represent the *min/max* values they can assume at year *t*. $S^{\max}$ is the maximum solar inverter rating.

-Capacity constraints at slack bus

$$P_b^{\min} \le P_{b,t} \le P_b^{\max} \qquad (13)$$

$$Q_b^{\min} \le Q_{b,t} \le Q_b^{\max} \qquad (14)$$

where $P_{b,t}$ and $Q_{b,t}$ are active and reactive powers at the slack bus at year *t*, respectively; $P_b^{\min} / P_b^{\max}$ and $Q_b^{\min} / Q_b^{\max}$ represent the *min/max* values they can assume.

-OLTC Tap limits

$$T_{ij}^{\min} \le T_{ij} \le T_{ij}^{\max} \qquad (15)$$

where T_{ij} is the tap magnitude of OLTC, $T_{ij}^{\min}$ and $T_{ij}^{\max}$ are respectively lower and upper limits they can assume.

-Power factor angle of PVs

$$\phi_g^{\min} \le \phi_{g,t} \le \phi_g^{\max} \qquad (16)$$

where $\phi_{g,t}$ is the power factor angle of PVs at year *t*, and $\phi_g^{\min} / \phi_g^{\max}$ are min/max values of power factor angle.

-DR constraint

$$0 \le P_{DR(l,t)}^{i} \le P_{DR(l)}^{i,\max} \quad (17)$$

$$0 \le Q_{DR(l,t)}^{i} \le Q_{DR(l)}^{i,\max} \quad (18)$$

where $P_{DR(l)}^{\max} / Q_{DR(l)}^{\max}$ are maximum active/reactive power decrement of load demand *l* at bus *i* in the DR context. The optimization variables of the multi-objective optimization problem include

vector $\mathrm{X} = (V_{i,t}, \delta_{i,t}, P_{g,t}^{i}, Q_{g,t}^{i}, P_{b,t}, Q_{b,t}, P_{DR(l,t)}^{i}, P_{DR(l,t)}^{i}, \phi_{g,t}, T_{ij})$.

VI. Case Study and Simulation Results

In this section, the distribution system used to test the proposed method is described. The following analyses are based on 33 kV 16-bus rural weakly meshed UKGDS whose data are available in [22]. The single-line diagram of the distribution system is shown in Fig.4. The feeders are supplied by two identical 30-MVA 132/33 kV transformers. Two OLTCs, allocated between buses 1 and 2, has a target voltage of 1.05 p.u. at the secondary. A voltage regulator (VR) is located between buses 8 and 9, with the latter having a target voltage of 1.03 p.u..Voltage limits are taken to be ±6% of nominal value, i.e. V_{min}= 0.94 and V_{max}= 1.06 p.u. and the power factor of PVs ranges from 0.95 leading to 0.95 lagging. The total peak demand is 38.2 MW. The cost of DR program paid to the customers to reduce their load demand for 10% at each bus is assumed to be 20£/MWh. The generation cost of PVs is assumed to be 10£/MWh. It is assumed that buses 5, 11 and 16 are three possible PV locations but it is notable that the selection of possible PV locations relies on non-technical factors such as legal requirements, space/land availability and other amenities. These three PV locations represent a load centre (at bus 5), a long feeder in urban area (at bus 11) and a rural area (at bus 16). Therefore, this choice provides different voltage rise/drop scenarios.

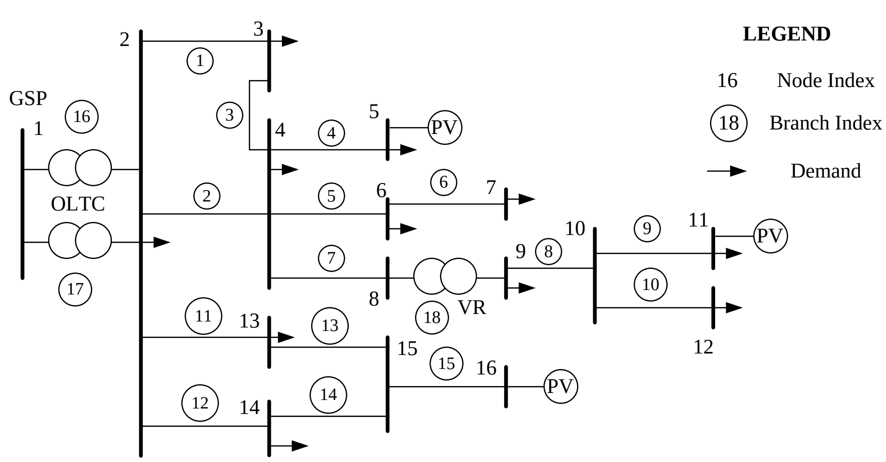
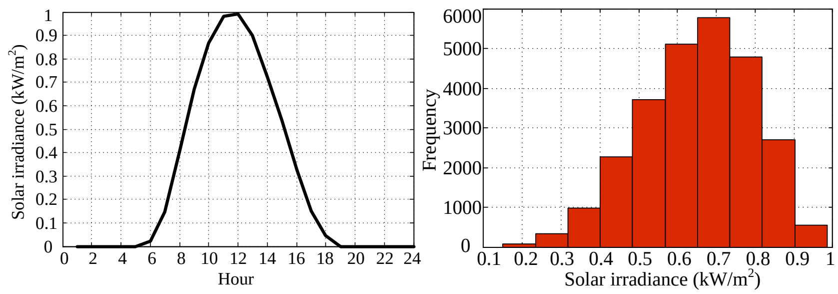


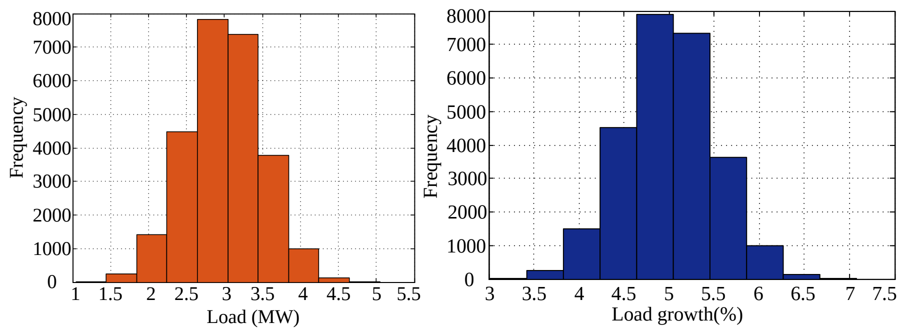
Fig.4. 16-bus UKGDS with candidate locations for PVs

Three 15 MW PVs are installed at buses 5, 11 and 16. Each of them is composed of $15\times1\text{MW}$ solar panels with $\eta^{pv}=18.6\%$ and $S^{pv}=10\,\text{m}^2$. The Beta PDF parameters of the solar irradiance are assumed to be α= 6.5, β = 3.5. The average hourly solar irradiance and the histogram of the Beta PDF of the considered solar irradiance are shown in Figs. 5 (a), 5(b), respectively. Load demand and load growth over the planning horizon are modeled by Normal PDF. The histogram of the PDF of load demand and load growth is shown in Figs. 6(a), 6(b), respectively.



(a) (b)

Fig.5. (a) hourly solar irradiance, (b) histogram of solar irradiance



(a) (b)

Fig.6. Histogram of (a) load demand, (b) load growth

The proposed method is applied to the abovementioned distribution network and implemented in GAMS and solved using IPOPT solver [23] on a PC with Core i7 CPU and 16 GB of RAM. The stochastic load demand and solar irradiance vary on hourly basis corresponding to 26280 (3×8760) samples of the MCS over the three-year planning horizon. In the sampling procedure, the possible sampling values are generated on hourly basis in year *t*. Note that each year of the planning horizon is equal to 8760 sampling hours. The method is on the basis of MCS technique considering different combinations of solar irradiance and load demand over the planning horizon. Particularly, on an hourly basis, 26280 samples with different combinations of solar irradiance and load demand are assumed. In order to investigate the impact of ANM schemes and DR program on total operational cost and energy losses, four different scenarios are taken into account as presented in Table I. The scenarios consider different combinations of ANM schemes and DR program. For each scenario, the total operational cost and energy losses of the network are examined.

TABLE I. SCENARIOS

Scenarios	CVC	PFC	Demand response	PF= 0.95 lagging
A	-	-	-	✓
B	✓	-	-	✓
C	✓	✓	-	-
D	✓	✓	✓	-

The sensitivity analysis is performed to choose the proper combination of the weighting factors in (5). The weighting factors are varied from 0.1 to 0.9 by steps of 0.05, so that $w_1+w_2=1$. Then, by solving the objective function (5) for each combination, the weighting combinations with the lowest values are selected. Analysis results are presented in Table II. It is worth noting that for various combinations of weightings, the values of objective functions are almost the same because of the non-convex optimality front. Therefore, in Table II, only the combinations are presented that their corresponding values for objective functions are different. It is observed from the table that the best set of weightings is w_1=0.3 and w_2=0.7. Moreover, it is obvious from Table II that the method is not very sensitive to the weightings selection.

TABLE II. SOLUTION OF THE OBJECTIVE FUNCTION WITH DIFFERENT COMBINATIONS OF WEIGHTINGS

Solution #	Weighting factor		Objective Functions	
	w_1	w_2	Operational Cost (£/h)	energy losses (kWh)
1	0.1	0.9	451.88	687.13
2	0.2	0.8	451.28	686.26
3	**0.3**	**0.7**	**451.20**	**685.94**
4	0.4	0.6	452.26	686.24
5	0.5	0.5	452.95	686.92
6	0.6	0.4	453.13	687.31
7	0.7	0.3	453.54	687.79
8	0.8	0.2	453.89	688.98
9	0.9	0.1	454.26	689.10

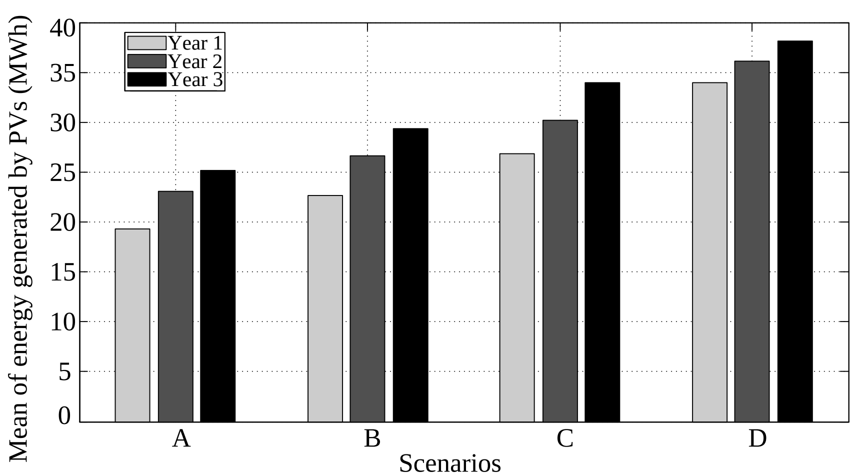


Fig.7. Mean of energy generated by PVs in different scenarios over the planning horizon

The mean of energy generated by PVs over the planning horizon in different scenarios is shown in Fig.7. Assuming an uncertain load growth for each year of planning horizon, the energy generated by PVs increases proportionally to load growth. It is seen that the energy generated with no ANM scheme during the last year of planning horizon is about 25 MWh while in scenario *B*, this value is about 30 MWh, thus, the energy generated by PVs increases about 20% compared to that in scenario *A*. Note that the energy generated by PVs is limited by the voltage and thermal limits of the lines. In scenario *C* (considering both CVC and PFC schemes) and the last year of planning horizon, the energy generated is almost 33 MWh, thus, energy generated increases about 32% compared to that with no ANM schemes. The impact of using both ANM schemes including CVC and PFC along with DR integration (Scenario *D*) on the energy generated by PVs is evident. In scenario *D* and the last year of the planning horizon, the energy generated is about 38 MWh which is increased about 50% compared to that in scenario *A*. Table III presents the objective functions in different scenarios. It is seen that in scenario *A*, the total operational cost and the total energy losses are respectively about 451 £/h and 686 kWh. In scenario *B*, these values respectively decrease about 11% and 10% compared to those in Scenario *A*. In scenario *C*, considering ANM schemes, the total operational cost and total energy losses are about 353 £/h and 583 kWh, respectively in which the decrement of the objective functions compared to those in Scenario *A* are about 21% and 15%. In scenario *D*, considering ANM schemes and DR program integration, the objective functions have the lowest values compared to those in other scenarios. The decrement of the total operational cost and total energy losses compared to those in scenario *A* are about 27% and 25%, respectively. As a result, by adopting ANM schemes and DR program integration, more PV energy can be generated and energy losses and total operational cost reduce compared to those in passive networks.

TABLE III. OBJECTIVE FUNCTIONS IN DIFFERENT SCENARIOS

Scenarios	Objective Functions	
	Total cost (£/h)	Energy losses (kWh)
A	451.20	685.94
B	401.17	622.36
C	353.55	583.78
D	326.72	512.65

VII. DISCUSSION AND CONCLUSION

In this paper, a probabilistic methodology based on MCS technique for the planning of active distribution networks with integration of DR considering ANM schemes is proposed. The method jointly minimizes total operational cost and total energy losses of the lines from the point of view of DNOs over the planning horizon taking into account uncertainties and network constraints. The stochastic nature of solar irradiance, load demand and future load growth are modelled by PDFs. MCS is utilized to use the generated PDFs and the weighting factor method is used to solve the multi-objective optimization problem.

ANM is considered as an important means of increasing the capability of distribution networks to install renewable DGs. In the future, ANM will characterize an efficient solution for DNOs to integrate and operate PVs in distribution networks, therefore, contributes to reducing the tensions between DG developers, who aim at maximizing their profits by increasing energy production, and DNOs, who aim at minimizing network operating and investment costs [24-28].

Results show that high penetration levels of PV generation capacity and cost and loss reduction can be reached by properly implementing ANM schemes and DR in comparison with the passive distribution networks.

It is worth noting that in order to choose the most proper ANM scheme, each scheme or a combination of them should be assessed taking into account the economic benefits under different scenarios. To assess of the economic feasibility of every scheme, the key elements to be taken into account including energy losses reduction in the network, increment of PV production and the benefits of network reinforcement strategies compared to those in passive distribution networks.

The method has been applied to larger networks which is not presented here and the results have proved the scalability of the proposed method and its applicability to larger networks. Moreover, it also can cope with a larger number of decision variables and even if this will result in increasing the computational burden but as the method is used for long-term planning studies this is not considered as a constraint.

Suppliers, aggregators or other industry parties will need to invest in systems and equipment to implement DR. This would include, for example, IT systems to communicate with smart meters, conveying the value of DR at any given time, and billing systems to be able to provide more sophisticated dynamic tariffs [29]. Therefore, the proposed method can be used as a tool for DNOs to evaluate the impact of PV penetration on a given network in terms of technical and economic effects as well as to better plan the integration of PVs into distribution networks. Moreover, the proposed method allows the decision makers to understand the implications of various choices on technical and economic performances of the distribution system.

REFERENCES

[1] The Modern Grid Initiative. Version 2.0, conducted by the National Energy Technology Laboratory for the US Department of Energy Office of Electricity Delivery and Energy Reliability; January 2007. http://www.netl.doe.gov/ moderngrid/resources.html.

[2] F. Saffre, R.Gedgein, "Demand side management for the smart grid" Proceedings of the 2010 IEEE IFIP network operations and management symposium workshops, pp. 300-303, 2010.

[3] B. Ramanathan, V. Vittal, "A framework for evaluation of advanced direct load control with minimum disruption", *IEEE Trans. Power Syst*., vol.23 no.4, pp.1681-1688, 2008.

[4] M. Marwan, F. Kamel, W. Xiang, "Mitigation of electricity price/demand using demand side response smart grid model" proceedings of the 1st international postgraduate conference on engineering, designing and developing the built environment for sustainable wellbeing, pp.1-6, 2011.

[5] G. Mokryani and P.Siano, "Evaluating the integration of wind power into distribution networks by using Monte Carlo simulation", *Int. J. Electr. Power Energy Syst.*, vol.53, pp.244-255, 2013.

[6] E. Haesen, C. Bastiaensen, J. Driesen, R. Belmans, "A probabilistic formulation of load margins in power systems with stochastic generation", *IEEE Trans. Power Syst*., vol.24, no.2, pp.951-958, 2009.

[7] J. Choi, T. Tran, A.A. El-Keib, R. Thomas, H. Oh, R. Billinton, “A method for transmission system expansion planning considering probabilistic reliability criteria”, *IEEE Trans Power Syst*., vol.20, no.3, pp.1606-1615, 2005.

[8] W. Wangdee, R. Billinton, “Considering load-carrying capability and wind speed correlation of WECS in generation adequacy assessment” *IEEE Trans Energy Convers.*, vol.21, no.3, pp.734-741, 2006.

[9] B. Khorramdel, M. Raoofat, “Optimal stochastic reactive power scheduling in a microgrid considering voltage droop scheme of DGs and uncertainty of wind farms”, *Energy*, vol.45, pp.994-1006, 2012.

[10] R. A B. Kirby, Spinning reserve from responsive loads Oak Ridge National Laboratory, ORNL/TM-2003/19, 2003.

[11] G. C. Heffner, C. A. Goldman, and A. M. M. Moezzi, “Innovative approaches to verifying demand response of water heater load control,” *IEEE Trans. Power Del.*, vol. 21, no. 1, pp. 388-397, 2006.

[12] C. Cecati, C. Citro, and P. Siano, “Combined operations of renewable energy systems and responsive demand in a smart grid,” *IEEE Trans. Sustain. Energy*, vol. 2, no. 4, pp. 468–476, 2011.

[13] C. Cecati, C. Citro, A. Piccolo, and P. Siano, “Smart operation of wind turbines and diesel generators according to economic criteria,” *IEEE Trans. Ind. Electron.*, vol. 58, no. 10, pp. 4514–4525, 2011.

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

[15] G. Mokryani, P. Siano, “Combined Monte Carlo Simulation and OPF for Wind Turbines Integration into Distribution Networks”, *Electr Power Syst Res.*, vol. 103, pp.37-48, 2013.

[16] F. A. Viawan and D. Karlsson, “Combined local and remote voltage and reactive power control in the presence of induction machine distributed generation,” *IEEE Trans. Power Syst.*, vol. 22, no. 4, pp. 2003–2012, 2007.

[17] Walling, R. Saint, R. C. Dugan, J. Burke, and L. A. Kojovic, “Summary of distributed resources impact on power delivery systems,” *IEEE Trans. Power Del.*, vol. 23, no. 3, pp. 1636-1644, 2008.

[18] F. Youcef, A. Mefti, A. Adane, M.Y. Bouroubi, “Statistical analysis of solar measurements in Algeria using beta distributions”, *Renew. Energy*, vol. 26, no.1, pp. 47-67, 2002.

[19] R. Chedid, H. Akiki, S. Rahman, “A decision support technique for the design of hybrid solar-wind power systems”, *IEEE Trans. Energy Convers.*, vol.13, no. pp. 76-83, 1995.

[20] T. Jamasb, K. Nuehoff, D. Newberry, and M. Pollitt, Long-Term Framework for Electricity Distribution Access Charges Report to Ofgem, Univ. Cambridge, Cambridge, U.K., 2005 [Online]. Available: http://www.electricitypolicy.org.uk/pubs/wp/eprg0507.pdf

[21] H. Morais, P. Faria, Z. Vale, “Demand response design and use based on network locational marginal prices”, *Int. J. Electr. Power Energy Syst.*, vol.61, pp.180-191, 2014.

[22] Distributed Generation and Sustainable Electrical Energy Centre, United Kingdom Generic Distribution System (UK GDS). [Online]. Available: http://www.sedg.ac.uk/.

[23] A. Brooke, D. Kendrick, A. Meeraus, R. Raman, “GAMS A User’s Guide”, GAMS Development Corporation, Washington DC, 1998.

[24] P. Siano, G. Mokryani, “Probabilistic assessment of the impact of wind energy integration into distribution networks,” *IEEE Trans. Power Syst.*, vol. 28, no. 4, pp. 4209-4217, 2013.

[25] P. Siano, G. Mokryani, “Assessing Wind Turbines Placement in a Distribution Market Environment by Using Particle Swarm Optimization”, *IEEE Trans. Power Syst.*, vol. 28, no. 4, pp. 3852-3864, 2013.

[26] P. Siano, G. Mokryani, “Evaluating the Benefits of Optimal Allocation of Wind Turbines for Distribution Network Operators”, *IEEE Syst. J.*, vol.9, no.2, pp.629-638, 2015.

[27] G. Mokryani, P. Siano, “Strategic Placement of DNO Owned Wind Turbines by Using Market-based Optimal Power Flow”, *IET Gener, Transm Distrib.*, vol.8, no.2, pp.281-289, 2014.

[28] G. Mokryani, P. Siano, “Optimal Wind Turbines Placement within a Distribution Market Environment”, Applied Soft Computing, vol.13, no.10, pp. 4038-4046, 2013.

[29] https://www.ofgem.gov.uk/sites/default/files/docs/2013/04/creating_the_right_environment_for_demand-side_response_0.pdf