Online Reconfiguration of Active Distribution Networks for Maximum Integration of Distributed Generation

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***Abstract*—This paper proposes the online reconfiguration of active distribution networks. The control of the active/reactive output power of distributed generation (DG) units combined with the control of remote controlled switches are employed in order to minimize DG curtailment, alleviate lines congestion, and mitigate voltage rise issues due to DG integration. Convex relaxations of the ac power flow equations and mixed integer linear disjunctive formulations are adopted to the optimization model in order to obtain fast and optimal solutions using standard branch and bound solvers. The computation burden of the optimization procedure is drastically reduced by exploiting the assessment of switching actions, which is performed using multiple load/generation scenarios. The effectiveness of the proposed optimization model is verified using different distribution test systems.**

***Note to Practitioners*—This work is motivated by the need for advanced network control and automation tools for the effective operation of power distribution networks with high distributed generation (DG) integration. The increasing penetration of variable DG, e.g., wind turbines and photovoltaics, can cause overvoltages and/or feeder overloads. To deal with these issues, current studies examine the control of the DG active and reactive power. DG curtailment is very effective to deal with voltage rise issues; however, it has financial consequences for DG owners and this can be a barrier to further DG penetration. This paper introduces a convex model for the online reconfiguration of active distribution networks that minimizes DG curtailment, relieves line congestion, and improves voltage profile. The proposed convex optimization model is applied to different distribution test systems. The results show that the application of the network reconfiguration as an active network management scheme can eliminate DG curtailment, which means that the exploitation of DG output power into the network is maximized.**

***Index Terms*—Active distribution network (ADN), active network management (ANM), distributed generation (DG), distribution network automation, distribution network reconfiguration (DNR), mixed integer nonlinear programming (MINLP).**

NOMENCLATURE

Sets

Ω_{DG}	Set of buses with distributed generation (DG).
Ω_L	Set of distribution lines.
Ω_{LnS}	Set of distribution lines without remote controlled switches (RCSs).
Ω_{LwS}	Set of distribution lines with RCSs.
Ω_N	Set of system buses.
Ω_{SS}	Set of substation buses.

Parameters

b_{ij}/g_{ij}	Susceptance/conductance of line $i - j$.
$I_{\max,ij}$	Ampacity of line $i - j$.
$P_{d,i}/Q_{d,i}$	Active/reactive load demand of bus i.
$P_{DG,i}$	Active power of the DG unit of bus i.
$P_{DGnom,i}$	Rated active power of the DG unit at bus i.
$Q_{DG\min,i}$	Minimum reactive power of the DG unit at bus i.
$Q_{DG\max,i}$	Maximum reactive power of the DG unit at bus i.
r_{ij}/x_{ij}	Resistance/reactance of line $i - j$.
$S_{DG\max,i}$	Maximum apparent power of the DG unit at bus i.
$S_{\max,ij}$	Thermal limit of line $i - j$.
$V_{\min}/V_{\max}$	Minimum/maximum voltage magnitude limits for network buses.
$V_{th,\min}/V_{th,\max}$	Minimum/maximum voltage thresholds for voltage deviation.
w_{dg}, w_l, w_v	Weighting coefficients.
$\theta_{\max}$	Maximum voltage angle difference.
$\phi_{\max}$	Maximum power angle of DG units.

Variables

$AuxU_{ij}$	Auxiliary variable associated with the power flow equations of line $i - j$.
cs_{ij}	Cosine relaxation variable of voltage angle difference between bus i and j.
$I_{sqr,ij}$	Current square magnitude of line $i - j$.
Im_{ij}	Imaginary part of the current of line $i - j$.
Ir_{ij}	Real part of the current of line $i - j$.

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$P_{DGcurt,i}$	Curtailment factor of the DG unit of bus i.
P_{ij}/Q_{ij}	Active/reactive power flow of line $i-j$.
$P_{SS,i}/Q_{SS,i}$	Active/reactive power injected from substation at bus i.
$Q_{DG,i}$	Reactive power of the DG unit of bus i.
sn_{ij}	Sine relaxation variable of voltage angle difference between bus i and j.
$U_{sqr,i}$	Voltage square magnitude of bus i.
UF_{ij}	Utilization factor of line $i-j$.
V_i	Voltage magnitude of bus i.
$V_{dev,i}$	Positive variable for the voltage deviation of bus i.
W_{ij}	Auxiliary variable associated with the product $V_i \cdot V_j$.
Wcs_{ij}	Auxiliary variable associated with the product $W_{ij} \cdot cs_{ij}$.
Wsn_{ij}	Auxiliary variable associated with the product $W_{ij} \cdot sn_{ij}$.
θ_i	Voltage angle of bus i.

Binary Variables

e_{ij}	Spanning tree variable. It is equal to 1 if bus j is the parent of bus i; otherwise it is equal to 0.
z_{ij}	Switch status of line $i-j$. It is equal to 1 if line $i-j$ is connected; otherwise it is equal to 0.

I. INTRODUCTION

IN RECENT years, both low and medium voltage distribution networks are facing the challenge to accommodate large shares of renewable distributed generation (DG), e.g., wind and photovoltaic, for the achievement of environmental goals [1]. Next to environmental benefits, the proper management of DG can reduce investment and operational costs of the distribution network. However, this ongoing shift to highly distributed and variable power generation demands advanced automation and control schemes, transforming the distribution networks from passive to active ones. The active distribution network (ADN) enables the coordinated control of DG, load, energy storage systems, and network components, such as on-load tap changers (OLTC) and remote controlled switches (RCSs) [2]. The active network management (ANM) can deliver solutions to the technical constraints violation caused by DG integration, deferring the necessary investments. Automated controls and switching actions are used to maintain the voltage within its limits, and manage the reverse power flows and the potential overloads caused by high DG penetration.

The implementation of ANM requires additional telecommunication and metering devices. Several ANM schemes have been proposed to highlight the potential benefits of the ADNs [3]–[7]. The main options of these ANM schemes for voltage regulation and feeder congestion relief are the coordination of the OLTCs with the control of the DG reactive power [3]–[5] and the curtailment of the DG active power [6], [7]. The DG active power curtailment is very effective for voltage constraint management due to the more resistive nature of the distribution network. However, this solution can be costly if the curtailed energy is to be compensated to the DG owners.

Distribution network reconfiguration (DNR) can be employed as an option for the mitigation of voltage rise issues and line congestions due to DG integration. A number of RCSs are allocated in modern power distribution networks to provide emergency connections and for reliability improvement [8]. RCSs constitute a significant component of the network automation and their control provides multiple network configurations. DNR has been used for power loss minimization [9]–[16], load balancing [9], [11], [16] reliability improvement [17], [18], fault isolation, and network restoration [19]–[21]. A multiobjective DNR formulation has been proposed in [22] that considers power loss minimization, load balancing, voltage drop minimization, service interruption frequency minimization, and balanced service of important customers. In [23], the proposed multiobjective DNR approach aims at minimizing the unsupplied loads and the power losses during a fault or an emergency condition. The control of capacitors, tie switches, and OLTC is proposed in [24] for optimal network operation in order to minimize network's power losses and voltage deviation. A fuzzy DNR formulation with multiple objectives is proposed in [25]. A stochastic multiobjective DNR approach is presented in [26] for systems with wind generation units and fuel cells. In the previous works, there is neither consideration of DG [9]–[12], [22]–[25] nor control of the DG output power [13]–[18], [26]. In [27], control of the active and reactive power of the DG units is considered and a network configuration is chosen from a predetermined set of network topologies in order to minimize the operational costs of the network. The combined control of RCSs, OLTCs, capacitors, and the active/reactive power of DG is proposed in [28] for voltage constraint management considering a multicriteria analysis. Furthermore, network reconfiguration is proposed for the maximization of the DG hosting capacity of the distribution network [29].

Optimal DNR is a complex optimization problem due to the large number of integer variables and the nonlinearity of the constraints. The offline network reconfiguration has been modeled as a nonconvex mixed integer nonlinear programming (MINLP) [10], [13] and approximate mixed integer linear programming [12] problem and it is solved by commercial branch and bound solvers. Furthermore, several heuristic algorithms have been proposed for the solution of the DNR for offline [9], [15], [25], [26] and online real-time [17], [18], [22] applications. An evolutionary multiobjective approach is used for online optimal network operation [24] and service restoration [23]. Although heuristic methods always yield a feasible solution, their optimality cannot be guaranteed. An approximate linearized model with continuous variables for the online active management of distribution networks considering specified multiple network topologies is presented in [27]. In [28], an online voltage control of ADNs considering network reconfiguration is formulated as MINLP nonconvex problem, leading in some cases, to suboptimal solutions due to time constraints. The DNR is formulated as a convex mixed integer conic programming (MICP) problem for passive distribution network in [11], [14], and [16]. Moreover, the DNR formulation proposed in [11] cannot be applied when there is bidirectional power flow.

In this paper, a convex model for the online reconfiguration of ADNs is introduced. Convex quadratic relaxations of the power flow equations are adopted in the DNR problem formulation. The proposed multiobjective optimization model includes the active management of the DG active/reactive output power and additional topological constraints that are not considered in [16]. The proposed method simultaneously integrates the optimal DNR with the DG control in order to improve the operational performance of the network in the presence of large shares of variable DG. The multiobjective function of the optimization procedure minimizes the weighted sum of the following three objectives: 1) DG active power curtailment; 2) line congestion; and 3) voltage deviation. Moreover, a data clustering method is employed to generate multiple representative load/generation scenarios in order to assess the appropriate number of control and switching actions of the optimization method. Therefore, the combinatorial search space is drastically reduced and along with the convexity of the optimization problem, the proposed framework can be applicable online by computing fast and optimal solutions further enhancing the distribution network automation. The effectiveness of the proposed methodology is demonstrated using the 34-bus, 70-bus, and 135-bus distribution test systems. Comparisons are also performed between the results of the proposed convex formulation and the exact MINLP formulation.

The main contributions and goals of this paper are as follows.

1) To propose the integration of DNR with the DG control, making use of convexification and online optimization. More specifically, an optimization model is proposed for the reconfiguration of ADNs that minimizes DG curtailment, relieves line congestion, and improves voltage regulation.
2) To introduce a convex formulation for the proposed optimization model. The convexification of the problem provides fast and reliable solutions making the proposed method applicable online.
3) To drastically reduce the combinatorial search space and the computation time and thus increase the performance by exploiting the assessment of switching actions, which is performed using multiple load/generation scenarios.

II. Distribution Network Reconfiguration

Power distribution networks are designed as meshed structures. However, they operate in radial configuration to simplify protection coordination. The distribution lines have normally closed switches and normally open switches. The DNR problem involves the selection of the optimal combination of open/closed switches in order to satisfy an optimization criterion. DNR for power loss minimization is a MINLP problem and it is formulated as follows [10], [13]:

$$\min \sum_{i\in\Omega_{SS}} P_{SS,i} \tag{1}$$

s.t.

$$P_{SS,i} - P_{d,i} = \sum_{j\in\Omega_N} z_{ij}\cdot P_{ij} \tag{2}$$

$$Q_{SS,i} - Q_{d,i} = \sum_{j\in\Omega_N} z_{ij}\cdot Q_{ij} \tag{3}$$

$$P_{ij} = g_{ij}V_i^2 - g_{ij}V_iV_j\cos(\theta_i-\theta_j) - b_{ij}V_iV_j\sin(\theta_i-\theta_j) \tag{4}$$

$$Q_{ij} = -b_{ij}V_i^2 + b_{ij}V_iV_j\cos(\theta_i-\theta_j) - g_{ij}V_iV_j\sin(\theta_i-\theta_j) \tag{5}$$

$$z_{ij}\cdot\left(Ir_{ij}^2 + Im_{ij}^2\right) \le I_{\max,ij}^2 \tag{6}$$

$$Ir_{ij} = g_{ij}(V_i\cos\theta_i - V_j\cos\theta_j) - b_{ij}(V_i\sin\theta_i - V_j\sin\theta_j) \tag{7}$$

$$Im_{ij} = g_{ij}(V_i\sin\theta_i - V_j\sin\theta_j) + b_{ij}(V_i\cos\theta_i - V_j\cos\theta_j) \tag{8}$$

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

$$\sum_{i,j\in\Omega_N} z_{ij} = |\Omega_N| - |\Omega_{SS}| \tag{10}$$

$$z_{ij} = 1,\quad \forall(i,j)\in\Omega_{LnS} \tag{11}$$

$$z_{ij}\in\{0,1\},\quad \forall(i,j)\in\Omega_{LwS} \tag{12}$$

The objective function of the power loss minimization problem where no DG is considered is given by (1). Equations (2) and (3) represent the active and reactive power balance for all $i\in\Omega_N$, respectively. The active and reactive power flow of the line that connects bus i with j are given in (4) and (5) for all $i,j\in\Omega_L$, respectively. The limit of the current magnitude is given in (6) for all $i,j\in\Omega_L$. The real and the imaginary part of the current are calculated as in (7) and (8), respectively, for all $i,j\in\Omega_L$. The bus voltage limits are defined by (9) for all $i\in\Omega_N$. The radial configuration of the network is ensured by (10). However, the radiality condition in (10) is insufficient in several cases [14] and it is properly addressed in the proposed optimization model (Section III-D). The binary variable z_{ij} is equal to 1 for all $i,j\in\Omega_{LnS}$ according to (11). Equation (12) declares the binary nature of the switch status for the lines that are equipped with them.

III. Proposed Optimization Model

The DNR formulation represented by (1)–(12) is a nonconvex MINLP problem. By introducing convexity into a problem, a branch and bound method can deliver a global optimum solution in less iterations and thus less computation time is needed. In this paper, convex quadratic relaxations for the nonlinear terms of the ac power flow equations (2)–(5) are employed with the addition of new variables [30]. Moreover, a disjunctive formulation is adopted to linearize the nonlinear mixed integer constraints of the reconfiguration problem [31], [32].

A. Convex Quadratic Relaxations of the AC Power Flow Equations

The quadratic term V_i^2 in (4) and (5) is relaxed into its convex envelopes for all $i\in\Omega_N$ as follows [30]:

$$U_{sqr,i} \ge V_i^2 \tag{13}$$

$$U_{sqr,i} \le (V_{\max}+V_{\min})\cdot V_i - V_{\max}\cdot V_{\min} \tag{14}$$

The quadratic relaxation of the cosine function for a small interval of angle differences is calculated for all $i, j \in \Omega_L$ as follows:

$$cs_{ij} \leq 1 - \frac{1 - \cos\theta_{\max}}{\theta_{\max}^2} \cdot (\theta_i - \theta_j)^2 \tag{15}$$

$$cs_{ij} \geq \cos\theta_{\max} \tag{16}$$

The relaxation of the sine function for all $i, j \in \Omega_L$ is determined by the following two inequalities:

$$sn_{ij} \leq \cos\left(\frac{\theta_{\max}}{2}\right) \cdot \left(\theta_i - \theta_j - \frac{\theta_{\max}}{2}\right) + \sin\left(\frac{\theta_{\max}}{2}\right) \tag{17}$$

$$sn_{ij} \geq \cos\left(\frac{\theta_{\max}}{2}\right) \cdot \left(\theta_i - \theta_j + \frac{\theta_{\max}}{2}\right) - \sin\left(\frac{\theta_{\max}}{2}\right) \tag{18}$$

McCormick convex envelopes are widely used for the relaxation of multilinear terms [32]. The bilinear term $V_i \cdot V_j$ in (4) and (5) is relaxed using the McCormick envelopes for all $i, j \in \Omega_L$ as follows:

$$W_{ij} \geq V_{\min} \cdot V_j + V_{\min} \cdot V_i - V_{\min} \cdot V_{\min} \tag{19}$$

$$W_{ij} \geq V_{\max} \cdot V_j + V_{\max} \cdot V_i - V_{\max} \cdot V_{\max} \tag{20}$$

$$W_{ij} \leq V_{\min} \cdot V_j + V_{\max} \cdot V_i - V_{\min} \cdot V_{\max} \tag{21}$$

$$W_{ij} \leq V_{\max} \cdot V_j + V_{\min} \cdot V_i - V_{\max} \cdot V_{\min} \tag{22}$$

The variable W_{ij} represents the McCormick relaxation of the product $V_i \cdot V_j$. Following the same method, Wcs_{ij} and Wsn_{ij} denote the convex relaxation of the bilinear terms $W_{ij} \cdot cs_{ij}$ and $W_{ij} \cdot sn_{ij}$, respectively.

The convex relaxations in (13)–(22) can be considered accurate since the angle difference and the bounds of the voltage limits are very narrow in the distribution networks. The ac power flow equations with the quadratic relaxations are defined for all $i, j \in \Omega_L$ as follows:

$$P_{ij} = g_{ij} U_{sqr,i} - g_{ij} Wcs_{ij} - b_{ij} Wsn_{ij} \tag{23}$$

$$Q_{ij} = -b_{ij} U_{sqr,i} + b_{ij} Wcs_{ij} - g_{ij} Wsn_{ij} \tag{24}$$

B. Disjunctive Mixed Integer Model for Distribution Network Reconfiguration

The variables P_{ij} and Q_{ij} in (23) and (24) are calculated for each distribution line that connects buses i and j. To model the network reconfiguration, the variables P_{ij} and Q_{ij} must be multiplied with the binary variable z_{ij}, which is equal to zero when the line $i - j$ is disconnected and is equal to 1 when the line $i - j$ is connected. However, by multiplying the status of the distribution line's switch (z_{ij}) with the variables P_{ij} and Q_{ij}, mixed-integer nonlinear constraints are inserted into the optimization model. Disjunctive formulations are employed to transform the mixed integer nonlinear constraints into mixed integer linear constraints for all $i, j \in \Omega_L$ as follows [31], [32]:

$$P_{ij} = g_{ij} AuxU_{ij} - g_{ij} Wcs_{ij} - b_{ij} Wsn_{ij} \tag{25}$$

$$Q_{ij} = -b_{ij} AuxU_{ij} + b_{ij} Wcs_{ij} - g_{ij} Wsn_{ij} \tag{26}$$

$$AuxU_{ij} \geq U_{sqr,i} - (1 - z_{ij}) \cdot V_{\max}^2 \tag{27}$$

$$AuxU_{ij} \leq U_{sqr,i} - (1 - z_{ij}) \cdot V_{\min}^2 \tag{28}$$

$$cs_{ij} \leq z_{ij} - \frac{1 - \cos\theta_{\max}}{\theta_{\max}^2} \cdot \left((\theta_i - \theta_j)^2 + (1 - z_{ij}) \cdot M_\theta^2\right) \tag{29}$$

$$cs_{ij} \geq z_{ij} \cdot \cos(-\theta_{\max}) - (1 - z_{ij}) \tag{30}$$

$$\begin{aligned} sn_{ij} &- M_{cs} \cdot (\theta_i - \theta_j) \\ &\leq z_{ij} \cdot \left(M_{sn} - M_{cs} \cdot \frac{\theta_{\max}}{2}\right) + (1 - z_{ij}) \cdot M_\theta \end{aligned} \tag{31}$$

$$\begin{aligned} -sn_{ij} &+ M_{cs} \cdot (\theta_i - \theta_j) \\ &\geq z_{ij} \cdot \left(M_{sn} - M_{cs} \cdot \frac{\theta_{\max}}{2}\right) + (1 - z_{ij}) \cdot M_\theta \end{aligned} \tag{32}$$

$$\begin{aligned} -(1 - z_{ij}) &+ z_{ij} \cdot \sin(-\theta_{\max}) \\ &\leq sn_{ij} \leq z_{ij} \cdot \sin\theta_{\max} + (1 - z_{ij}) \end{aligned} \tag{33}$$

$$(\theta_i - \theta_j) \leq z_{ij} \cdot \theta_{\max} + (1 - z_{ij}) \cdot M_\theta \tag{34}$$

$$(\theta_i - \theta_j) \geq -z_{ij} \cdot \theta_{\max} - (1 - z_{ij}) \cdot M_\theta \tag{35}$$

$$M_\theta = |\Omega_L| \cdot \theta_{\max} \tag{36}$$

$$M_{cs} = \cos\left(\frac{\theta_{\max}}{2}\right) \tag{37}$$

$$M_{sn} = \sin\left(\frac{\theta_{\max}}{2}\right) \tag{38}$$

The reformulated active and reactive power flow equations of line $i - j$ are defined by (25) and (26), respectively. The disjunctive formulation of the voltage square magnitude is given by (27) and (28). Moreover, the linear disjunctive model of the cosine function relaxation is represented by (29) and (30). The disjunctive version of the sine function relaxation is given by (31)–(38).

C. DG Active/Reactive Power Control

The active management of DG is an efficient method for overvoltage mitigation. It is implemented in the optimization model for all $i \in \Omega_{DG}$ as follows:

$$Q_{DG,i} \geq -P_{DG,i} \cdot P_{DGcurt,i} \cdot \tan\phi_{\max} \tag{39}$$

$$Q_{DG,i} \leq P_{DG,i} \cdot P_{DGcurt,i} \cdot \tan\phi_{\max} \tag{40}$$

$$0 \leq P_{DGcurt,i} \leq 1 \tag{41}$$

$$Q_{DG\max,i} = P_{DGnom,i} \cdot \tan\phi_{\max} \tag{42}$$

$$Q_{DG\min,i} = -P_{DGnom,i} \cdot \tan\phi_{\max} \tag{43}$$

$$S_{DG\max,i}^2 = P_{DGnom,i}^2 + Q_{DG\max,i}^2. \tag{44}$$

The range of the injected DG reactive power is given by (39) and (40). The bounds of the curtailment factor are given by (41). The maximum and minimum limits of the DG reactive power injections are presented in (42) and (43), respectively. In (44), the maximum apparent power of the inverter is given.

Due to the resistive feature of the distribution networks, the voltage deviation is more sensitive to active power than to reactive power. Consequently, DG curtailment is very effective in voltage regulation.

D. Proposed Active Distribution Network Reconfiguration

In this paper, the network reconfiguration is introduced as an advanced tool for ANM and network automation. Modifying the network topology provides more efficient management of the power flows, minimization of the energy losses, and voltage deviation, leading to better exploitation of the network assets.

The proposed convex optimization model for the reconfiguration of ADNs is as follows:

$$\min \sum_{i\in\Omega_{DG}} w_{dg}\cdot(1-P_{DGcurt,i}) + \sum_{i,j\in\Omega_N} w_l\cdot \mathrm{UF}_{ij} + \sum_{i\in\Omega_N} w_v\cdot V_{dev,i} \tag{45}$$

s.t.

$$P_{SS,i}+P_{DG,i}-P_{DGcurt,i}-P_{d,i} = \sum_{j\in\Omega_N}(g_{ij}AuxU_{ij}-g_{ij}Wcs_{ij}-b_{ij}Wsn_{ij}) \tag{46}$$

$$Q_{SS,i}+Q_{DG,i}-Q_{d,i} = \sum_{j\in\Omega_N}(-b_{ij}AuxU_{ij}+b_{ij}Wcs_{ij}-g_{ij}Wsn_{ij}) \tag{47}$$

$$P_{ij}+P_{ji}=I_{sqr,ij}\cdot r_{ij} \tag{48}$$

$$Q_{ij}+Q_{ji}=I_{sqr,ij}\cdot x_{ij} \tag{49}$$

$$P_{ij}^2+Q_{ij}^2\le I_{sqr,ij}\cdot U_{sqr,i} \tag{50}$$

$$P_{ij}^2+Q_{ij}^2\le z_{ij}\cdot I_{sqr,ij}\cdot V_{\max}^2 \tag{51}$$

$$P_{ij}^2+Q_{ij}^2\le z_{ij}\cdot S_{\max,ij}^2 \tag{52}$$

$$P_{ij}^2+Q_{ij}^2\le S_{\max,ij}^2\cdot \mathrm{UF}_{ij} \tag{53}$$

$$V_{dev,i}\ge U_{sqr,i}-V_{th,\max}^2 \tag{54}$$

$$V_{dev,i}\ge -U_{sqr,i}+V_{th,\min}^2 \tag{55}$$

$$e_{ij}+e_{ji}=z_{ij},\quad (i,j)\in\Omega_{LwS} \tag{56}$$

$$\sum_{j\in\Omega_N} e_{ij}=1,\quad i\in\Omega_N\backslash\Omega_{SS} \tag{57}$$

$$e_{ij}=0,\quad i\in\Omega_{SS} \tag{58}$$

$$e_{ij}\in\{0,1\} \tag{59}$$

as well as the constraints defined by (9), (11)–(14), (19)–(22), and (27)–(44). The control variables of the proposed MICP model are: 1) the statuses of the RCSs (z_{ij}), which are binary variables; 2) the active power curtailment factors of the DG units ($P_{DGcurt,i}$), which are continuous variables; and 3) the reactive power outputs of the DG units ($Q_{DG,i}$), which are continuous variables.

The objective function (45) aims at minimizing the active power curtailment of the DG units, the feeder power flow, and the voltage deviation along the feeder. The minimization of the DG active power curtailment in fact maximizes the integration of the power produced by the DG units. The analytic hierarchy process (AHP) method [34] is employed to calculate the weighting coefficients of each term of the multiobjective function (45). In the AHP method, the decision maker (DM) performs a pairwise comparison between the objectives and defines their importance in comparison with the rest of the objectives.

The new active and reactive power node balance are given by (46) and (47) for all $i\in\Omega_N$, respectively. Equations (48) and (49) are used to strengthen the assumed relaxations by providing redundancy to the formulation for all $i,j\in\Omega_L$ [16]. The square of the current magnitude is defined by the conic constraint (50) and its disjunctive counterpart (51) for all $i,j\in\Omega_L$ [30]. The maximum thermal capacity of the distribution lines is given by (52) for all i, $j\in\Omega_L$. The utilization factor of each distribution line is calculated according to (53) for all $i,j\in\Omega_L$. The variable associated with the voltage deviation is determined by (54) and (55) for all $i\in\Omega_N$. The radial configuration of the distribution network is guaranteed by (56)–(59) for all $i,j\in\Omega_L$ [14]. It is assumed that the distribution network is a spanning tree and the substation is considered as the root of the tree. For the line $i-j$ that is connected to the spanning tree ($z_{ij}=z_{ji}=1$), the bus i can be the parent of bus j ($e_{ji}=1$) or the bus j can be the parent of bus i ($e_{ij}=1$), as shown in (56). Every bus can have only one parent according to (57), while the substation bus has no parents as (58) indicates. The binary nature of variable e_{ij} is given by (59). The proposed convex formulation for the reconfiguration of ADNs enables the bidirectional power flow of the lines, which was not addressed in the problem solved in [11]. Furthermore, in this paper, network reconfiguration is employed as an additional ANM scheme, an aspect that was not addressed in [14] and [16].

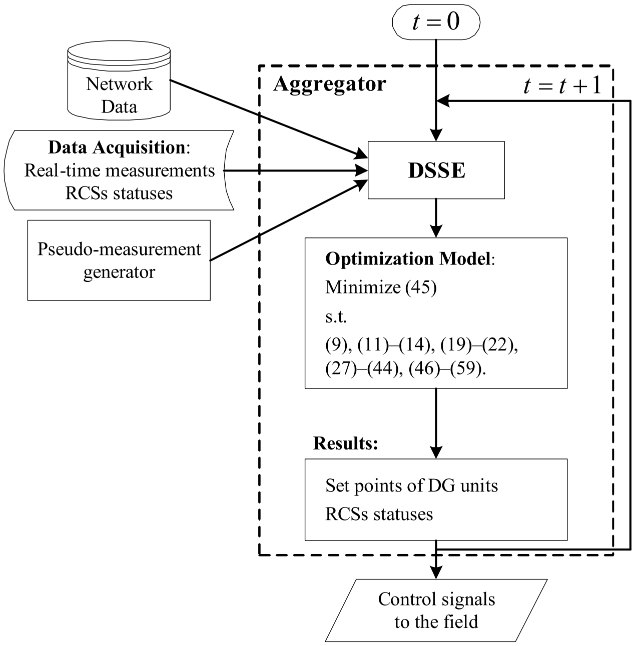

Fig. 1. Control network structure.

The smart control of the power systems improves their technical and economic efficiency [35]. Fig. 1 illustrates the practical approach and structure of the communication and network automation that supports the optimization model. As shown in Fig. 1, an aggregator controls the DG units and the network components. During the time-interval defined (e.g., 1 h or 15 min), the aggregator solves online the optimization problem using as input the acquired data. A distribution system state estimator (DSSE) is integrated. The DSSE receives real-time measurements from the advanced metering infrastructure installed in the distribution network and with the proper deployment of pseudomeasurements the network status is defined [36]. The proposed optimization framework uses as input the DSSE output data and the technical constraints of the network. The results of the optimization model are the set points of the DG units and the statuses of the RCSs, which are sent as control signals to the field, i.e., the local controllers of the DG units and RCSs.

E. Assessment of Control and Switching Actions

The offline DNR formulation in [11], [14], and [16] considers both manual and RCSs as decision variables leading to a large combinatorial space and high computation time. In order to make the reconfiguration of ADN applicable online, the assessment of the control and switching actions is estimated in a preliminary (planning) stage using multiple load/generation scenarios. Considering these scenarios, an offline analysis of the proposed optimization model (Section III-D) is performed in order to identify which RCSs do not participate in the optimization procedure, i.e., which RCSs never change their statuses. As a result, the number of control variables is limited, which drastically decreases the computation burden of the optimization procedure.

A reasonable number of scenarios should be examined in order to account for the volatility of the input data. However, accounting for a large number of load/generation scenarios (e.g., yearly data) leads to impractical and numerous simulations. In this paper, the *kmeans* clustering method [37] is employed to classify the available data and provide a suitable number of scenarios. The *kmeans* clustering method partitions the given set of m-dimensional data into k clusters. The derived k clusters contain data with similar features and the centroid of each cluster represents the average behavior of its included data.

IV. RESULTS AND DISCUSSION

The performance of the proposed methodology is tested using the modified 34-bus [9], 70-bus [38], and 135-bus [39] distribution test systems. The proposed optimization model has been developed in MATLAB 2012a and GAMS [40] using CPLEX solver [41]. All the tests have been carried out on a PC with an Intel Core i7 CPU at 3.40 GHz and 4 GB of RAM.

In order to quantify the benefits of considering the network reconfiguration as an ANM scheme and the assessment of switching actions, the results of the three cases are analyzed for all the above distribution test systems. These three cases are as follows.

1) *Case I:* The control of the active and reactive power output of the DG units is considered as an ANM scheme.
2) *Case II:* The network reconfiguration and the control of the active and reactive power output of the DG units are considered as ANM schemes. All the available RCSs are considered as control variables in the optimization procedure.
3) *Case III:* The network reconfiguration and the control of the active and reactive power output of the DG units are considered as ANM schemes. The RCSs with zero switching probability in Case II are not considered as control variables.

A. Input Data Clustering

The hourly load profile for one year of the network is presented in Fig. 2. The hourly solar and wind generation profiles for one year are shown in Figs. 3 and 4, respectively. The data of Figs. 2–4 were acquired from the case study of [42]. The data are divided into 50 clusters using *kmeans* method (Section III-E) resulting in 50 load/generation scenarios. The centroids of the clusters are taken as the load/generation scenarios and the occurrence probability of each scenario is computed. The number of clusters was chosen using trial and error method. A higher number of clusters results in almost identical simulation results for the given data of Figs. 2–4, though requiring higher computation time.

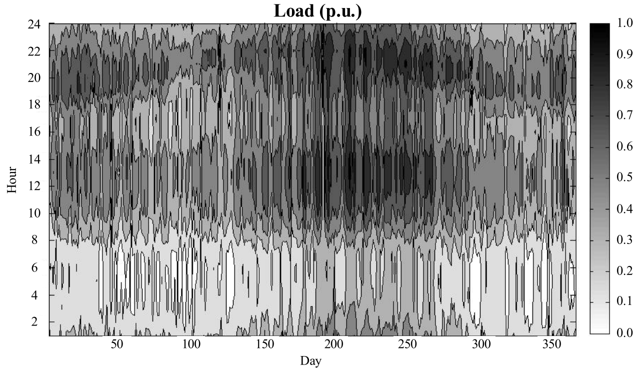

Fig. 2. Yearly load profile.

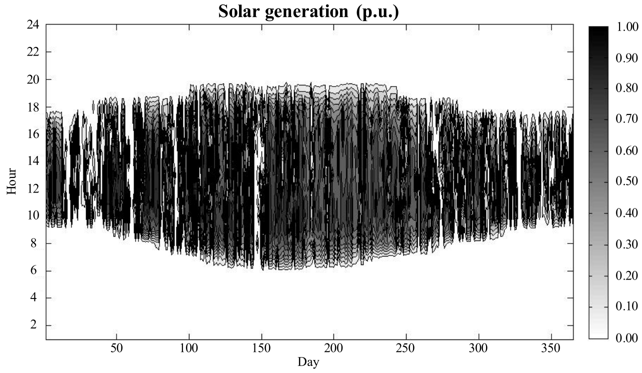

Fig. 3. Yearly solar generation profile.

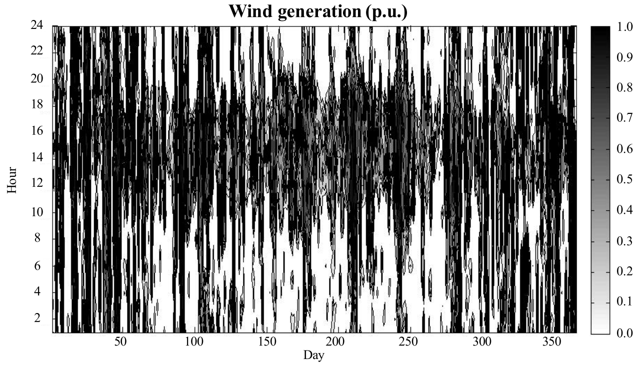

Fig. 4. Yearly wind generation profile.

The *kmeans* clustering is performed using the *k-means* function of MATLAB's Statistics and Machine Learning toolbox. The *kmeans* function uses Lloyd's algorithm [43] and the cluster center initialization is performed using the

TABLE I

PAIRWISE COMPARISON OF THE OBJECTIVE TERMS OF (45)

	DG active power curtailment	**Feeders' utilization factor**	**Voltage deviation**	**Weighting coefficients**
DG active power curtailment	1	7	8	0.777
Feeders' utilization factor	1/7	1	3	0.153
Voltage deviation	1/8	1/3	1	0.070

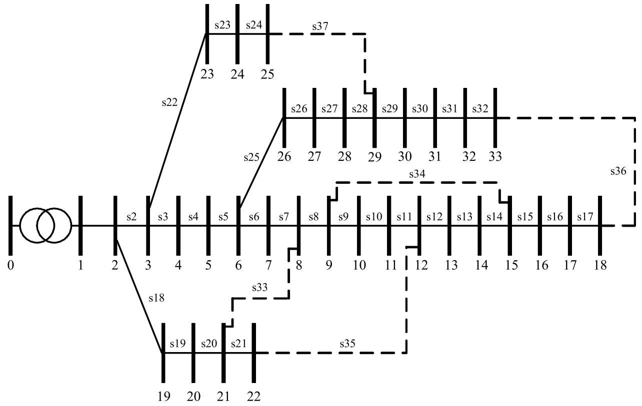

Fig. 5. Modified 34-bus distribution test system.

TABLE II

PERFORMANCE COMPARISON OF CASES I–III FOR THE 34-BUS DISTRIBUTION SYSTEM

	Case I	**Case II**	**Case III**
Annual Curtailed Energy from DG units (MWh)	953	0	0
Annual Energy Losses (MWh)	1 512	745	745
Annual Energy Flow via Substation (MVAh)	17 323	14 557	14 557

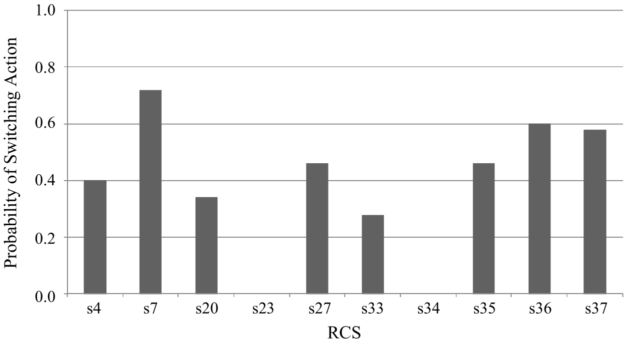

Fig. 6. Switching probability of the RCSs installed in the 34-bus distribution test system.

squared Euclidean distance measure and the *kmeans++* algorithm [44].

B. Weighting Coefficient Calculation

The AHP method calculates the weight values for each objective of (45). First, pairwise comparisons between the objectives of (45) are performed with respect to the overall goal. The pairwise comparisons are presented in Table I. As shown in the first row in Table I, the DM, e.g., the Distribution System Operator, on a scale from 1 to 9, considers DG curtailment as 7 and 8 times more important than feeders' utilization factor and voltage deviation, respectively. Similarly, the second row in Table I shows that the DM considers feeders' utilization factor as 3 times more important than voltage deviation. The weights of (45) are calculated using the AHP method and their values are presented in the last column in Table I. The consistency index is equal to 0.052. In fact, the calculated weighting coefficients give the relative priority of the multiple objectives of (45) and determine the relative merit of each objective in the optimal solution. The optimization procedure minimizes (45) considering the given priorities.

C. Modified 34-Bus Distribution Test System

The 34-bus distribution system (see Fig. 5) is a 12.66 kV system with 37 lines, 32 switches, and 5 tie switches. The peak load is 3.715 MW and 2.3 Mvar. The voltage limits are equal to ±5% of the nominal voltage and the thermal capacity of each line is considered 6 MVA. The voltage thresholds for voltage deviation minimization are ±3%. The system was modified as follows:

1) Seven solar DG units of 100 kW are connected at buses 21, 22, 24, 25, 28, 29, and 30.
2) One wind DG unit of 5 MW is connected at bus 18.
3) All five tie switches as well as the switches s4, s7, s20, s23, and s27 are considered as RCSs.

Table II reports the results of Cases I–III, which include the estimated annual energy curtailment from the DG units, the annual energy losses and the annual energy flow through the substation based on the 50 load/generation scenarios (Section IV-A).

In the preliminary stage, i.e., Case II, the assessment of the switching actions is performed. The proposed optimization model (Section III-D) is executed for 50 simulations considering as input the 50 aforementioned load/generation scenarios derived from the clustering of the data presented in Figs. 2–4. Afterward, the switching probability of the RCSs is calculated based on the occurrence probability of each scenario. Fig. 6 presents the probability of each RCS to change its status. The reference network topology is the initial one of Fig. 5. The average computation time of the 50 simulations in Case II is 12.23 s. However, as shown in Fig. 6, the switches s23 and s34 do not participate at all in the optimization procedure, since they have zero switching probability. Therefore, they can be excluded from the control variable list of the optimization model in order to significantly reduce the computation burden. Thus, s23 and s34 are excluded from the control variable list in Case III and the average computation time is equal to 8.21 s, i.e., reduced by 32.87% compared to Case II. Furthermore, as shown in Table II, there is no difference between the results of Cases II and III.

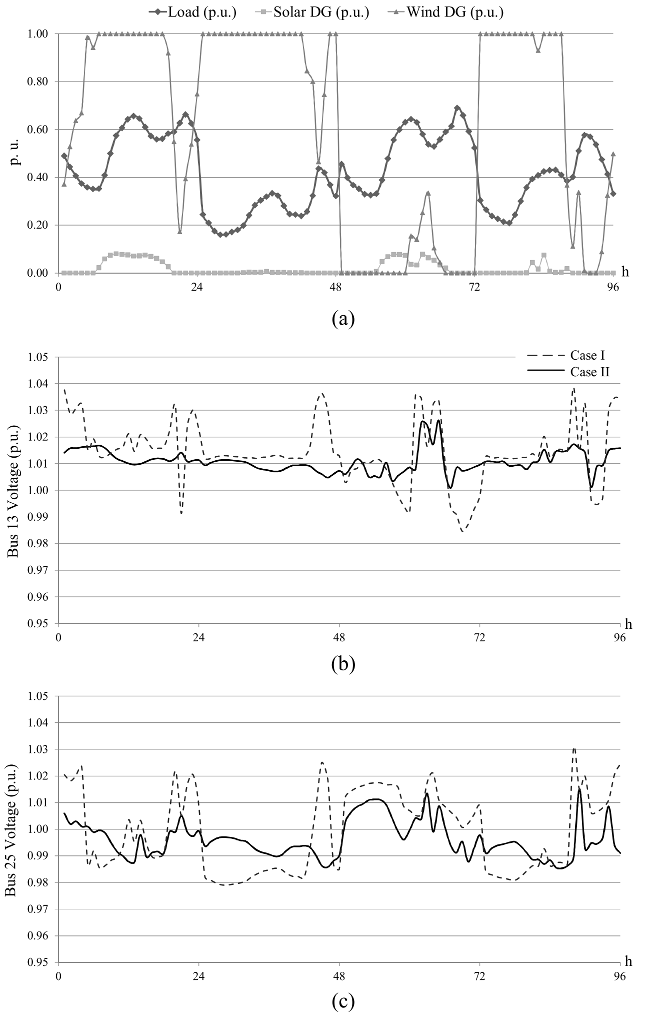

Fig. 7. (a) Load, wind, and solar generation profiles (p.u.) of the four days. (b) Voltage profile of bus 13. (c) Voltage profile of bus 25 of the 34-bus distribution test system.

In Case I, as shown in Table II, the estimated energy curtailment is 953 MWh, which corresponds to substantial loss of income for the DG owner or a barrier to the DG penetration, if the curtailed energy has to be compensated. However, the consideration of the network reconfiguration as an ANM scheme (Cases II and III) completely eliminates the energy curtailment. Apart from the elimination of the energy curtailment of the DG units, the online reconfiguration (Case III) reduces the energy losses by 50.73% and the power flow via the substation by 15.97% compared to Case I.

The effect of the network reconfiguration on the system's voltage profile is demonstrated by employing the proposed optimization procedure for four days of the year with different characteristics. The four days, shown in Fig. 7(a), correspond to the following.

1) *Day 1:* Maximum load and maximum DG.
2) *Day 2:* Minimum load and maximum DG.
3) *Day 3:* Maximum load and minimum DG.
4) *Day 4:* Average load and average DG.

The voltage profile of buses 13 and 25 for these days are presented in Fig. 7(b) and (c), respectively. The dashed line represents the voltage profile for Case I and the solid line represents the voltage profile for Case III. As shown in Fig. 7(b) and (c), the employment of network reconfiguration as ANM scheme (Case III) minimizes the voltage deviation. Moreover, the voltage magnitude of the buses in Case III is kept close to its nominal value improving the power quality to the end-customers.

TABLE III

RCSs INSTALLED IN THE 70-BUS DISTRIBUTION SYSTEM

#	From *i*	To *j*	#	From *i*	To *j*
s1	5	6	**s10**	66	67
s2	4	10	**s11**	22	67
s3	18	19	**s12**	15	67
s4	17	23	**s13**	21	27
s5	33	34	**s14**	9	50
s6	32	39	**s15**	29	64
s7	54	55	**s16**	45	60
s8	52	57	**s17**	38	43
s9	62	63	**s18**	9	15

TABLE IV

PERFORMANCE COMPARISON OF CASES I–III FOR THE 70-BUS DISTRIBUTION SYSTEM

	Case I	Case II	Case III
Annual Curtailed Energy from DG units (MWh)	541	0	0
Annual Energy Losses (MWh)	1 572	1 257	1 258
Annual Energy Flow via Substations (MVAh)	24 407	22 780	22 782

D. Modified 70-Bus Distribution Test System

The 70-bus distribution system is an 11 kV system with two substations, four feeders, 68 load buses and 78 distribution lines [38]. The system was modified as follows.

1) The peak load of the system is the 80% of the load presented in [38].
2) Eleven solar DG units of 100 kW are connected at buses 6, 7, 8, 26, 27, 28, 29, 40, 41, 58, and 59.
3) One wind DG unit of 4 MW is connected at bus 38.
4) Eighteen switches are considered as RCSs, as shown in Table III.

The results of Cases I–III for the 50 aforementioned load/generation scenarios are presented in Table IV. The 50 load/generation scenarios are derived from the clustering of the data presented in Figs. 2–4. In Case II, the average computation time of the 50 simulations is 757 s. The switching probability of each RCS of the distribution system is calculated using these 50 load/generation scenarios and the results are presented in Fig. 8. The computation time can be decreased if the RCSs with zero switching probability, i.e., s4, s6, and s13

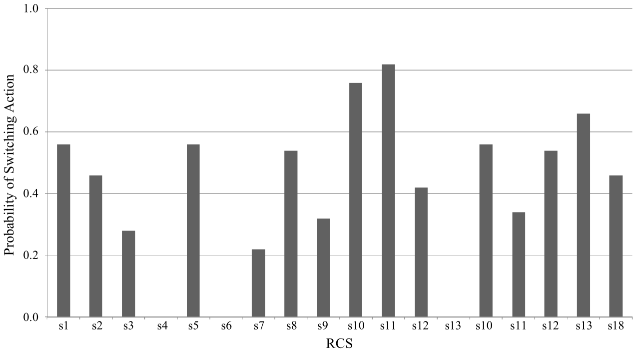

Fig. 8. Switching probability of the RCSs installed in the 70-bus distribution test system.

are excluded from the list of the control variables. Indeed, these five variables are omitted from the control variable list in Case III and the average computation time for the 50 simulations drops to 323 s, which is 57.33% lower compared to the 757 s. By excluding these five variables, the simulation results of Cases II and III are not affected, as shown in Table IV.

The curtailed energy from the DG units is equal to zero when the network reconfiguration is considered as ANM scheme (Cases II and III), as shown in Table IV, while in Case I the estimated annual energy curtailment is 541 MWh. Moreover, comparing the results of Cases I and III, it is noted that the annual energy losses and the annual energy flow through the substations are reduced by 20.04% and 6.67%, respectively, if the control of the RCSs and the active/reactive output power of the DG units is considered.

E. Modified 135-Bus Distribution Test System

The 135-bus distribution system is a 13.8 kV system with two substations, 8 feeders, 107 load buses, 28 zero injection buses and 156 distribution lines [39]. The peak load of the system is 18.31 MW and 7.94 Mvar. The system was modified as follows.

1) The total rated power of the solar DG units that are connected to the network is 22 × 100 kW.
2) The total rated power of the wind DG units that are connected to the network is 14 MW.
3) All the 21 tie switches are considered as RCSs and each feeder is considered to be equipped with three RCSs. Thus, the total number of RCSs is equal to 45.

The results of Cases I–III for the 135-bus distribution system are presented in Table V. The available data of Figs. 2–4 are grouped into 50 clusters. These 50 load/generation scenarios were used as input data for the proposed optimization procedure. The average computation time in Case II is 1069 s. The obtained results of Case II indicate that 10 out of the 45 RCSs have zero switching probability. In Case III, these 10 RCSs are excluded from the control variable list. As a result, the computation time in Case III is decreased to 564 s, which is 47.24% lower compared to 1069 s and the simulation results of Cases II and III are almost identical, as shown in Table V.

Performing a comparison between the results of the three cases, it is noticed that the energy curtailment from the DG units is eliminated when the network configuration is considered as an ANM scheme (Cases II and III). Otherwise, the annual energy curtailment is 238 MWh (Case I). Furthermore, the annual energy losses and the annual energy flow through the substation are reduced by 36.92% and 5.16%, respectively, when the online reconfiguration of ADNs is adopted (Case III).

TABLE V
PERFORMANCE COMPARISON OF CASES I–III FOR THE 135-BUS DISTRIBUTION SYSTEM

	Case I	**Case II**	**Case III**
Annual Curtailed Energy from DG units (MWh)	238	0	0
Annual Energy Losses (MWh)	1 926	1 215	1 217
Annual Energy Flow via Substations (MVAh)	69 789	66 186	66 193

F. Comparison of Exact and Convex Formulation

The proposed optimization model is based on the convex relaxations of the nonlinear terms of the ac power flow equations and mixed integer disjunctive formulations, as presented in Section III. The exact nonconvex MINLP model consists of the objective function (45) subject to the constraints (2)–(9), (11), (12), (39)–(44), and (56)–(59). The results of the exact MINLP model are compared with the results of the proposed optimization model in order to investigate the quality and the accuracy of the proposed model with the convex relaxations. The comparison of results for Case II is shown in Tables VI and VII. Bonmin solver [45] was used to solve the exact MINLP model.

Table VI presents the objective value, the power losses, and the computation time of the proposed convex model and the exact MINLP model for three load/generation scenarios out of the 50 scenarios of Section IV-A. These three load/generation scenarios are the following.

1) *Scenario 1:* 0.79 p.u. load demand; 0.58 p.u. solar generation; and 0.89 p.u. wind generation.
2) *Scenario 2:* 0.52 p.u. load demand; 0.59 p.u. solar generation; and 0.58 p.u. wind generation.
3) *Scenario 3:* 0.30 p.u. load demand; 0.00 p.u. solar generation; and 0.32 p.u. wind generation.

As shown in Table VI, the two models provide practically the same value for the objective function and the power losses. Table VII also confirms the close agreement for the results of the two models. Table VI shows that the solution of the proposed model requires notably less computation time than the exact model, which is a strong advantage for the proposed model that is intended for online use. Due to the narrow bounds of the voltage limit and the small bus angle difference in distribution networks, the proposed method adequately approximates the results of the exact MINLP method. It should be noted that in all the test cases the initial solutions were generated automatically by the solver.

TABLE VI

OBJECTIVE, POWER LOSSES, AND COMPUTATION TIME FOR THE 34-BUS, 70-BUS, AND 135-BUS DISTRIBUTION TEST SYSTEMS FOR CASE II

	34-bus		**70-bus**		**135-bus**	
	MINLP	Proposed	MINLP	Proposed	MINLP	Proposed
	Scenario 1					
Objective	0.162	0.162	0.136	0.134	0.166	0.163
Power losses (MW)	0.301	0.301	0.455	0.451	0.210	0.205
Time (s)	88	11	1 006	501	2 741	949
	Scenario 2					
Objective	0.125	0.125	0.147	0.144	0.230	0.226
Power losses (MW)	0.134	0.133	0.287	0.276	0.128	0.121
Time (s)	120	16	1 107	754	1 932	1 073
	Scenario 3					
Objective	0.045	0.045	0.070	0.070	0.040	0.040
Power losses (MW)	0.033	0.033	0.074	0.074	0.026	0.026
Time (s)	78	14	1 739	102	815	77

TABLE VII

RESULTS COMPARISON BETWEEN THE MINLP AND THE PROPOSED MODEL FOR THE 34-BUS, 70-BUS, AND 135-BUS DISTRIBUTION TEST SYSTEMS FOR CASE II

	34-bus		**70-bus**		**135-bus**	
	MINLP	Proposed	MINLP	Proposed	MINLP	Proposed
Annual Curtailed Energy from DG units (MWh)	0.0	0.0	0.0	0.0	0.0	0.0
Annual Energy Losses (MWh)	771	745	1 272	1 257	1 285	1 215
Annual Energy Flow via Substation (MVAh)	14 815	14 557	23 108	22 780	66 973	66 186
Average Time (s)	83	12	1 685	757	2 263	1 069

V. CONCLUSION

This paper proposes the online network reconfiguration as an additional ANM scheme of ADNs for the minimization of DG curtailment, line congestion relief, and voltage rise mitigation due to high DG penetration. Convex relaxations are adapted to the optimization model for fast and accurate solutions. Moreover, the assessment of switching actions is implemented using multiple load/generation scenarios. The load/generation scenarios were generated by the *kmeans* data clustering method in order to account for the stochastic behavior of both load and DG. The assessment of switching actions significantly reduces the combinatorial search space decreasing the computation burden of the optimization procedure. Different distribution test systems are used to validate the performance of the proposed method.

The obtained results show that the proposed reconfiguration of ADNs can eliminate DG curtailment, reduce the annual energy losses, and improve the voltage profile. Another remarkable result is that by properly limiting the switching actions, the optimal solutions are computed very fast using an ordinary desktop computer and a commercial branch and bound solver. Thus, the proposed optimization model can be applicable online.

Taking into account the effectiveness of the proposed model, it is concluded that network reconfiguration is a valid solution for the management of ADNs. Network reconfiguration, as an ANM scheme, maximizes the DG integration into the network, while it defers potential network investments and decreases operational costs.

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