NETWORK RECONFIGURATION UNDER A STOCHASTIC OPTIMISATION FRAMEWORK FOR DAY-AHEAD OPERATION PLANNING FOR FUTURE DISTRIBUTION NETWORKS

Gregorio HIGUERA-GUTIERREZ
Durham University, UK
gregorio.higuera-gutierrez@durham.ac.uk

Behzad KAZEMTABRIZI
Durham University, UK
behzad.kazemtabrizi@durham.ac.uk

ABSTRACT

This paper proposes a novel Active Network Management (ANM) framework for day-ahead operations planning of a medium-voltage active Distribution Network (DN) using a heuristic Network Reconfiguration (NR) algorithm with a Curtailment Minimisation Scheme (CMS) to maximise utilisation of renewable Distributed Generation (DG) resources. The reconfiguration scheme uses Back-to-Back Voltage Source Converters (BTB-VSCs) in the network as Soft Open Points (SOP) which are modelled mathematically using the Flexible Universal Branch Model (FUBM) developed previously in Durham University. Moreover, this day-ahead ANM framework takes into account the variable nature of RES outputs by adopting a stochastic multi-scenario formulation using the Inverse Transform Method and Stratified Sampling to generate power output realisations for the RES. Simulations carried out for a modified IEEE-33 distribution test system shows the proposed ANM framework is capable of reducing operational costs by 2.22% to the system operator whilst actively regulating the voltage throughout the network and reducing curtailment in medium and high power output scenarios.

INTRODUCTION

The worldwide climate policy has widely adopted a Net-Zero focus. Many countries have pledged and set targets to reduce Greenhouse Gas (GHG) emissions to achieve Net-Zero by 2050 [1], [2]. One of the main paths to achieve this goal is the total decarbonisation of electricity by a transition to Renewable Energy Resources (RES) as Distributed Generation (DG) in electrical networks [3], [4]. However, this transition and high integration of RES will pose new operational challenges for the existing infrastructure. Amongst the main operational challenges facing operators are power variability and intermittency of RES, low network flexibility and voltage and thermal limits violations [3], [5]–[7]. These problems are more evident in Medium and Low Distribution Networks (DNs) where there is a high susceptibility to voltage fluctuations due to its high coupling with real power injection [6], [7]. It is in this context that new management frameworks such as Active Network Management (ANM) start to appear more relevant in recent years for Distribution System Operators (DSOs) to manage their distributed resources while addressing these new operational challenges.

One of the ANM frameworks that have drawn attention to reinforce networks is Network Reconfiguration (NR) using Soft Open Points (SOPs). SOPs are essentially Power Electronics Devices (PEDs) that are placed at strategic points in the DNs to provide flexible power flow control and fast response to unforeseen changes in power supply and demand [8], [9]. In contrast with traditional equipment such as On Load Tap Changing (OLTC) Transformers, capacitor banks and Remote Controllable Switches (RCSs) which may be operationally limited due to their discrete nature and physical constrains, SOPs are much more flexible in their operation [9]. The form of SOPs that have been explored and researched in previous works are the Back-to-Back Voltage Source Converters (BTB-VSCs). For instance, the capabilities of the BTB-VSCs for load balancing between adjacent feeders using soft-meshing was explored and compared with RCSs in [5]. In the work of [6], the BTB-VSCs were used for voltage profile regulation and abating power congestion through a NR framework for daily operations planning for DNs. Moreover, in [10] the topology was used to minimise losses and reduce phase imbalance in DNs. Alternatively, the common DC-link formed by the BTB-VSCs was used in [7] to create a Multi-Terminal DC (MTDC) network within the DNs to increase the hosting capacity for DGs. Thus, making the topology of BTB-VSCs advantageous for a large variety of applications, including NR frameworks, addressing current challenges in DNs.

For this paper, the contributions are as follows

- Development of an ANM Framework which addresses current operational challenges in DNs using Curtailment Minimisation Scheme (CMS) for Distributed Generators (DGs) and a NR Framework for day-ahead operations planning.
- Integration of a Stochastic Optimisation Framework to the ANM to address technical challenges of high DG RES integration.
- Development of novel ANM approaches for future DNs with high penetration of RES.

ACTIVE NEWORK MANAGEMENT FRAMEWORK

This section will present the ANM Framework used for this work which consists of a heuristic Network Reconfiguration (NR) strategy based on the work carried out in [6] and a Curtailment Minimisation Scheme (CMS) to maximise power generation from the DGs.

The BTB-VSCs used for the NR scheme were mathematically modelled using the Flexible Universal Branch Model (FUBM) developed by Alvarez-Bustos et. al [11], [12] previously developed in Durham University for MATLAB/MATPOWER adding extra degrees of freedom for modelling control capabilities of BTB-VSCs needed for effective NR implementation.

Network Reconfiguration

To improve the performance of the DNs by increasing their flexibility, a NR scheme is implemented in this work. The original scheme was implemented by Ibrahim A. et. al. in [6] using the Advanced Interactive Multidimensional Modeling System (AIMMS) software. However, this scheme imposes a Mixed Integer Non-Linear Programming (MINLP) problem which the current version of MATPOWER is not capable of solving and is inherently computationally expensive [13]. Thus, a heuristic approach has been developed to implement the NR scheme using MATPOWER without the need for formulating the problem as a MINLP. The implementation of the NR scheme is based on a heuristic algorithm, the configuration of controlled lines ($\mathcal{C}$) and radiality constraints. There are two radiality constraints that must ensure the radial topology of the distribution network is preserved. The Initial Radial State Constraint (IRSC) shown in Eq. (1) ensures that the number of active controlled lines c at any time t will be equal as the initial state s_c^0.

$$\sum_{c\in\mathcal{C}} s_c^t = \sum_{c\in\mathcal{C}} s_c^0 \qquad t \in \mathcal{T} \tag{1}$$

In Eq. (1), the set $\mathcal{T}$ is the set of all time-periods within a set planning time and $\mathcal{C}$ is the set of all controlled lines. The IRSC shown in Eq. (1) on its own might be insufficient to ensure radiality because it can isolate buses from the Grid Supply Point (GSP) [6]. Consequently, the Active Paths Constraint (APC) is implemented to guarantee radiality. The APC ensures that at least one *k-th* path π_k^i in the *i-th* region Π^{i} is connected to the GSP. The APC is shown in the Eq. (2).

$$\Pi^{r,t} = \sum_{k=1}^{K} \pi_k^{r,t}(s_c) \geq 1 \qquad r \in \mathcal{R}, t \in \mathcal{T} \tag{2}$$

In Eq. (2), the set $\mathcal{R}$ is the set of all regions of the network that should be connected to the GSP. Both constraints are evaluated in the NR algorithm shown in Fig. 1. Essentially, this algorithm will filter possible configurations with the radiality constraints and then heuristically evaluate these configurations using the FUBM to set up the active paths with the BTB-VSC looking for the configuration that has the minimum operational cost. With the FUBM, voltage and power controls are applied to the BTB-VSCs to actively regulate the AC voltage and limit the active power across the arrangement, respectively. It should be noted that this approach does not impose a true MINLP optimisation problem in contrast with the work done in [6].

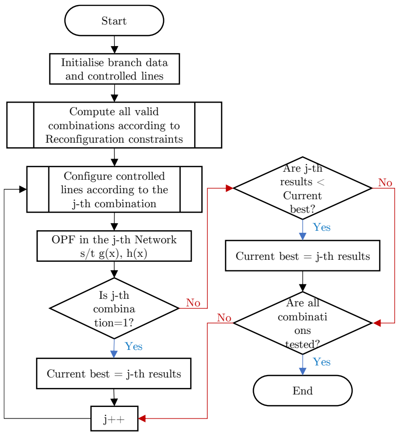

Fig. 1. Network Reconfiguration algorithm flowchart.

Curtailment Minimisation Scheme for DGs

To reduce the curtailment actions on the DGs, a curtailment variable $\boldsymbol{\zeta}$ is added to the optimisation problem for all DGs ($\mathcal{G}$). The variable $\boldsymbol{\zeta}$ bounds and constraints are described in the Eq. (3).

$$\begin{aligned} 0 \leq \zeta_i \leq P_{max}^i \qquad & i \in \mathcal{G} \\ \zeta_i = P_{max}^i - P_g^i \qquad & i \in \mathcal{G} \end{aligned} \tag{3}$$

In Eq. (3), the set $\mathcal{G}$ is the set of all active DG in the network. Furthermore, a quadratic cost function is also added for ζ. This function calculates the total cost of curtailment for all generators with $\{\mathbf{Q_z}, \mathbf{c_z}, \mathbf{k_z}\}$ forming the vectors of cost coefficients. The total curtailment cost is shown in the Eq. (4).

$$f_{curt}(\zeta) = \zeta^{\intercal} diag(\boldsymbol{Q_z})\zeta + \boldsymbol{c_z}^{\intercal}\zeta + \boldsymbol{k_z} \tag{4}$$

where $Q_z^i \in \mathbf{Q_z}$, $c_z^i \in \mathbf{c_z}$ and $k_z^i \in \mathbf{k_z}$ are the cost coefficients that define the quadratic function for each DG. The matrix $\mathrm{diag}(\mathbf{Q_z})$ is a diagonal matrix with all diagonal elements being the elements of $\mathbf{Q_z}$. The main objective of this cost function is to respond to curtailment values given by Eq. (3). Thus, minimising the values in $\boldsymbol{\zeta}$ will minimise the costs of $f_{curt}(\zeta)$.

ANM IMPLEMENTATION: A MULTIPERIOD STOCHASTIC OPTIMISATION

As it has been said in previous sections, the high penetration of RES based DG increases the level of uncertainty and intermittency within the DNs. As uncertainty increases, the stakeholders in the network may have to make decisions under uncertain scenarios such as the level of demand, power generation and electrical market prices which lower the overall efficiency, security, and reliability of the DNs [9], [14], [15]. For this reason, new ANM frameworks should be able to handle a certain degree of uncertainty to work accordingly with the new DNs. Stochastic Optimisation methods provide tools to model and optimise decisions under uncertainty [16].

Stochastic Scenario Generation

To implement the stochasticity of RES DG profiles into the ANM framework, multi-scenario matrices D_q are introduced. These D_q matrices are populated with power output scenarios $\omega_t^{q,j}$ generated by using the inverse transform and stratified sampling methods. The scenarios $\omega_t^{q,j}$ are generated as

$$\omega_t^{q,j} = F_{\mathcal{W}}^{-1}(z_t^{q,j}) \qquad j \in \mathcal{J},\, t \in \mathcal{T}, q \in \mathcal{Q} \tag{5}$$

In Eq. (5), $\mathcal{J}$ is the set of all generated scenarios for the stochastic analysis, $\mathcal{Q}$ is the set of all segments or intervals used for the stratified sampling method, $z_t^{q,j}$is a random sample drawn at time t for the *j-th* scenario with uniform distribution from the *q-th* segment and $F_{\mathcal{W}}^{-1}$ is the Inverse Cumulative Distribution Function (ICDF) of the random variable of interest $\mathcal{W}$. Then, the D_q matrix is defined as a $(N_t \times N_j)$ matrix for each q segment. Eq. (6) shows the multi-scenario matrix

$$D_q = \begin{bmatrix} \omega_1^{q,1} & \cdots & \omega_1^{q,j} & \cdots & \omega_1^{q,N_j} \\ \vdots & \ddots & \vdots & & \vdots \\ \omega_t^{q,1} & \cdots & \omega_t^{q,j} & \cdots & \omega_t^{q,N_j} \\ \vdots & & \vdots & \ddots & \vdots \\ \omega_{N_t}^{q,1} & \cdots & \omega_{N_t}^{q,j} & \cdots & \omega_{N_t}^{q,N_j} \end{bmatrix} \tag{6}$$

In this work, this matrix is used as an input parameter for generating multiple scenarios representing variable RES DG profiles thereby making the overall ANM planning framework into a stochastic optimisation problem.

General Objective Cost Function

The stochastic optimisation problem implemented as the ANM framework in this paper can be simply stated as

$$\min_{x} \mathbb{E}(\hat{C}_{dso}(\boldsymbol{x})) \qquad \boldsymbol{x}^{\intercal} = [\Theta, V, P_g, Q_g, \zeta] \tag{7}$$

where $\boldsymbol{x}$ is the state variables vector and $\hat{C}_{dso}(\boldsymbol{x})$ is the general cost function for the DSO that is currently formed by two components

$$\hat{C}_{dso}(\boldsymbol{x}) = f_g(P_g, Q_g) + f_{curt}(\zeta) \tag{8}$$

the first element $f_g(P_g, Q_g)$ is the sum of individual polynomial cost functions f_P^i and f_Q^i of real power and reactive power injections for each DG, respectively. This cost function is stated as

$$f(P_g, Q_g) = \sum_{i \in \mathcal{G}} [f_P^i(p_g^i) + f_Q^i(q_g^i)] \tag{9}$$

Moreover, the second element $f_{curt}(\zeta)$ was explained in Eq. (4). Additionally, the expected cost value $\mathbb{E}(\hat{C}_{dso})$ from the simulations will be also contemplated. This expected cost value will consider N_j total number of scenarios and N_t total number of time-periods. It will be computed as follows

$$\mathbb{E}(\hat{C}_{dso}) = \frac{1}{N_j}\sum_{j \in \mathcal{J}} \frac{1}{N_t} \sum_{t \in \mathcal{T}} \sum_{i \in \mathcal{G}} [f_g^{jti}(P_g^{jti}, Q_g^{jti}) + f_{curt}^{jti}(\zeta^{jti})] \tag{10}$$

The proposed Active Network Management (ANM) framework implemented in this paper essentially solves a multi-period stochastic optimisation problem (in form of an Optimal Power Flow) with the goal of minimising the cost in objective function in Eq. (10) below subject to the networks realistic operational and physical limits (i.e., the nodal power balance equations).

CASE STUDY AND RESULTS

The case study and simulations are carried out in MATLAB environment using the MATPOWER [17] for solving power flow and OPF problems. The distribution test system used as a benchmark for the simulations is the IEEE 33-bus distribution system [18]. The network case data was modified to include 6 DGs throughout the network to simulate high penetration of RES for a total DG capacity of *6 MW* (*1 MW* each). The DGs and load profiles used for the simulated cases can be found in Appendix (A). Moreover, 10 controlled lines have been included using FUBM for the NR scheme. The modified IEEE 33-bus distribution test system used in this work is shown in the Fig. 2. For the stochastic simulation and analysis, UK onshore wind power data have been used from the period of 01-01-2010 to 31-12-19 [19]. Furthermore, a seasonal approach has been considered due to the differences in power outputs from the onshore wind resources throughout the year. The seasonal datasets used for the analysis are from summer and winter extracted from the main dataset mentioned earlier. Likewise, these datasets were segmented by wind level power output using stratified sampling for generating multiple scenarios of wind resource for the simulation as per Eq. (5) and (6).

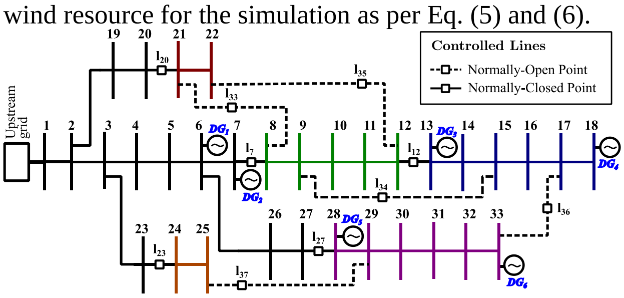

Fig. 2. Modified IEEE 33-bus distribution test system including 6 DGs and controlled lines for network reconfiguration.

For the proof of concept, deterministic simulation cases were run using MIPS 1.4 (MATPOWER Interior Point Solver) developed by Zimmerman R. and Wang H. [13] on a PC with an Intel Core CPU at 2.5GHz with 8GB RAM.

Curtailment Minimisation Scheme

To test this feature of the proposed ANM, a comparison on the DGs' output is done by simulating the distribution test system with and without using the CMS. Two cases are analysed: (I) power curtailed on the DGs and (II) scheduled generation at the Grid Supply Point (GSP) in a day-ahead operations planning framework. Both cases' results are shown in Fig. 3 and in TABLE 1.

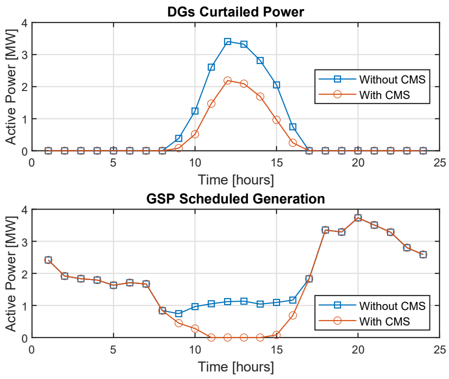

Fig. 3. CMS: Curtailed power on DGs and scheduled generation of GSP in day-ahead operations planning.

The results indicate that there is a lower degree of curtailment on the DGs when using the CMS. The total reduction of power curtailed over the 24-hour planning is *7.32 MW* which represents *44%* reduction from the simulation case that is not using CMS. Then, the same amount of power is reduced from the scheduled generation at the GSP reaching a scheduled generation of *0 MW* in the hours of peak generation of the DGs (see Appendix A).

TABLE 1. Results of simulations using CMS.

Using CMS?	DGs curtailed power [MW]	GSP scheduled gen. [MW]
No	16.57	46.51
Yes	9.25	39.71

Also, it can be noted that in the case where the CMS is active, there is still power being curtailed because the load is being fully served at that time and power curtailment is unavoidable. For instance, a viable way to avoid curtailment in this condition is to sell the power surplus to the DSO in an energy transactive framework.

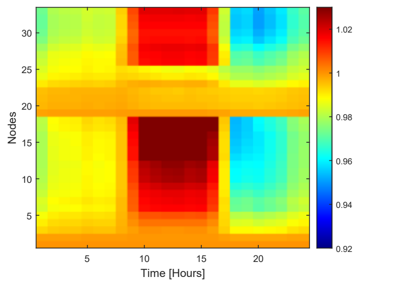

Fig. 4. Network Voltage Profile in Normal Operation (i.e., no NR).

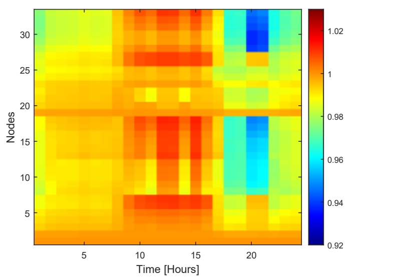

Fig. 5. Network Voltage Profile using NR with RCSs.

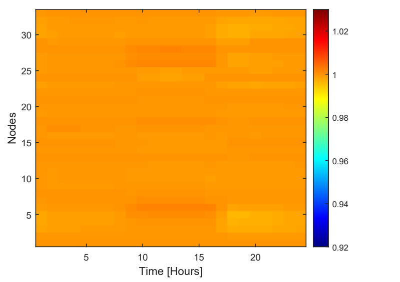

Fig. 6. Network Voltage Profile using NR with BTB-VSCs.

Distribution Network Voltage Profile

To evaluate the voltage profile, three simulation cases for comparison are carried out: (I) Normal operation (i.e., no NR), (II) NR using conventional RCSs and (III) NR using BTB-VSCs. The voltage profile maps from the three cases are shown in Fig. 4, Fig. 5, & Fig. 6, respectively. For the normal operation case (Fig. 4), it can be seen that the voltage magnitude is more variable through the day for the nodes far from the GSP (e.g., nodes $12 \rightarrow 18$ & $28 \rightarrow 33$). This is caused by the changes in the load and generation conditions especially in the peak generation hours and by the end of the day. For instance, these nodes got the global minimum voltage magnitude value of *0.93 p.u.* at the lowest generation point ($t = 20$) and the global maximum voltage magnitude value *1.04 p.u.* at the highest generation point ($t = 13$). As for the NR with RCSs case (Fig. 5), the voltage magnitude has a better performance through the network due to the NR including the farthest nodes. Also, the switching action of the RCSs can be noticed as the voltage magnitude is not as smooth and progressive as the first case results. This is due to the NR algorithm that will look for the configuration which better performs in terms of costs so the network topology might change from time t to time $t+1$. For case using NR with BTB-VSCs (Fig. 6), the voltage magnitude remains almost constant throughout the network and over the entire operation time-horizon as the BTB-VSCs are regulating the buses' voltage magnitude actively. Hence, making active electrical branch elements such as VSCs the best option for NR or similar flexibility control strategies. The global minimum and maximum voltage magnitudes values for all three cases for comparison are presented in TABLE 2.

TABLE 2. Global voltage magnitudes values from simulations.

Global Voltage Magnitudes (p.u.)			
Voltage	Normal Op.	NR-RCSs	NR-BTBVSCs
MIN	0.9505	0.9378	0.9963
MAX	1.0446	1.0125	1.0019

Operational Planning Costs

The cases for the analysis of operational planning costs are as follows: (I) Normal operation, (II) NR using RCSs, (III) Normal operation using BTB-VSCs and (IV) NR using BTB-VSCs. The results for the day-ahead operation planning of the simulation cases are shown in Fig. 7 and in TABLE 3.

TABLE 3. Operational planning costs for simulation cases.

Simulation case	Normal Operation	NR using RCSs	Normal operation using BTBVSCs	NR using BTBVSCs
Expected cost **($/hr)**	56.22	55.90	57.94	56.65

To make a one-to-one comparison between the cases with and without BTB-VSCs, the switching losses G_{sw} from the VSCs have been neglected even though in practice these losses are an inherent characteristic of switching PEDs. As it is shown in Fig. 7, all cases have similar cost profile which tell that seamlessly integration of the BTB-VSCs is achieved through the FUBM. Furthermore, considering the results in *TABLE 3*, it can be noticed on how the costs have been reduced in both instances where NR have been used being 0.59% in the cases without BTBVSCs and 2.22% in the cases with them. Thus, proving the action of the NR algorithm on reducing costs and indicating that is more cost efficient when using BTB-VSCs for its control actions in a day ahead operations planning.

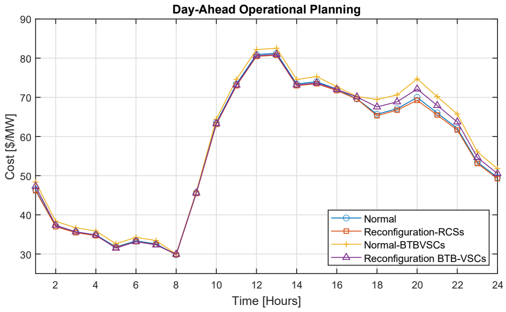

Fig. 7. Day-ahead operation planning hourly costs from simulation cases.

Stochastic Simulation

The stochastic simulations were done in a High-Performance Computing (HPC) machine suitable for large scale parallel calculations and simulations. The results from the simulations are summarised in TABLE 4.

TABLE 4. Stochastic framework simulation results.

			Reconfiguration BTB-VSC			No reconfiguration BTB-VSC		
Season	Wind level	Scenarios #	Power curtailed (MW/hr)	DG use (%/hr)	Operational costs ($/hr)	Power curtailed (MW/hr)	DG use (%/hr)	Operational costs ($/hr)
SUMMER	LOW	100	0.0025	98.4	55.22	0.0011	99.52	56.31
		500	0.0026	98.28	55.2	0.0011	99.48	56.32
		1000	0.0027	98.35	55.22	0.0012	99.47	56.34
	MID	100	0.0445	90.05	55.12	0.0535	88.09	55.52
		500	0.0442	90.1	55.13	0.0528	88.23	55.51
		1000	0.0432	90.27	55.11	0.0519	88.35	55.49
	HIGH	100	0.2396	66.33	58.25	0.2478	64.94	59.33
		500	0.2424	65.97	58.19	0.2493	64.77	59.35
		1000	0.2422	66.04	58.21	0.2493	64.81	59.36
WINTER	LOW	100	0.0034	98.24	54.97	0.0017	99.3	56.04
		500	0.0031	98.28	54.99	0.0017	99.33	56.01
		1000	0.0035	98.13	54.9	0.0017	99.33	55.98
	MID	100	0.0539	88.53	55.28	0.0658	86.04	55.7
		500	0.0546	88.36	55.24	0.0656	86.12	55.7
		1000	0.0549	88.34	55.22	0.066	86.03	55.7
	HIGH	100	0.2776	63.11	58.96	0.2798	62.55	60.15
		500	0.2793	62.95	58.96	0.281	62.48	60.19
		1000	0.2788	63.04	58.99	0.281	62.5	60.2

According to the results of TABLE 4, in the instances of MID and HIGH wind scenarios the NR framework is capable to keep a higher degree of DG use (i.e., reducing curtailment) whilst reducing operational costs in comparison with the simulation cases operating without the NR. Although in the LOW wind scenarios a lower use of DG is exhibited, the NR framework still ensures a lower operational cost per hour as it is the algorithm main objective.

CONCLUSIONS

In this paper, a fully operating ANM framework for network operations planning to tackle operational challenges introduced by the extensive use of RES in DNs has been presented. The main challenges addressed by the developed ANM are regarding voltage fluctuations, low efficiency in the use of RES, low network flexibility, and uncertainty on power generation from the RES. The simulations results indicate that the proposed ANM framework is capable of ensuring lower operational costs when using NR for all cases and increasing the DG use (i.e., reducing curtailment) in conditions of medium and high wind power. Also, it is capable to actively regulate the voltage avoiding fluctuations throughout the DN by using the BTB-VSCs. Thus, the developed ANM framework is successfully addressing current operational challenges thereby incentivising higher levels of RES DG integration in active DNs

APPENDICES

Appendix A

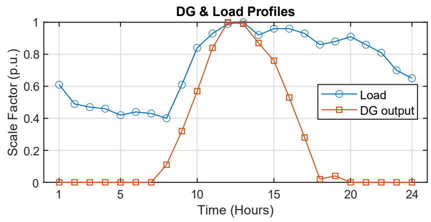

Fig. 8. DG and load profiles used for the simulation cases.

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