Seasonal Grid Reconfiguration for Optimal DSO Operations in High Solar PV Scenarios

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Abstract—**This study proposes a strategy for seasonal grid reconfiguration, evaluating configurations optimized for distinct seasonal conditions and varying levels of Photovoltaic (PV) production. A Non-dominated Sorting Genetic Algorithm II (NSGA-II) algorithm is employed to identify optimal configurations, generating a range of configurations that form a Pareto-front of solutions. This method allows for a comparison of seasonal configurations against the baseline configuration, enabling a robust assessment of the benefits of periodic reconfigurations in dynamic Distributed Energy Resource (DER) environments. The findings reveal a couple of configurations that perform best across all seasons, delivering significantly lower energy losses and improved voltage profiles compared to the baseline configuration, with improvements superior to 30%. These results suggest that network efficiency and voltage profiles can be improved without frequent reconfigurations, indicating that optimal configurations are robust to DER variability.**

Index Terms—**Distributed energy resource, Distribution network reconfiguration, Optimal grid configuration, Renewable energy integration, Seasonal network reconfiguration**

I. INTRODUCTION

As DER penetration increases, Distribution System Operators (DSOs) are compelled to adopt more dynamic grid configurations to adapt to varying load and generation conditions. Traditionally, DSOs rely on an “Optimal Configuration” determined during the planning stage, which is generally static and only modified in cases of system faults or critical grid restrictions. However, maintaining a static configuration under diverse and variable DER conditions can lead to suboptimal performance in terms of energy losses and voltage profiles. The operation of distribution networks has been significantly transformed by the increasing penetration of DERs, such as PV systems [1].

The traditional structure of power systems, characterized by hierarchical generation, transmission and distribution, is being challenged by the integration of these types of resources [2]. With effect, the traditional power systems were designed to support unidirectional energy flows.

The problem is that with the integration of other production units at the distribution level, such as Distributed Generation (DG) units, which are small generating units that are powered by renewable energy sources, such as solar, the energy flow starts to be bidirectional, and that may lead to fluctuations in the voltage levels and increased energy losses [3]. Moreover, the volatility that these types of resources introduce also contributes to more constraints in the distribution system operation.

Therefore, there is a pressing need to develop new strategies for reconfiguring the distribution grid to ensure the optimal integration of DERs, while maintaining grid stability and reliability [2], [3].

Distribution Network Reconfiguration (DNR) is a possible strategy to be used. It refers to the process of redefining the layout of the distribution system, by changing the status of the switches that compose the system, and finding configurations that present better characteristics of operation, such as fewer power losses and better voltage profiles, thereby increasing the integration of DERs in power systems [4]. DNR is an optimization problem that can be either single-objective [5]-[7], if the objective function only has one objective, or multi-objective [8]-[10], if the objective function has more than one objective.

To solve the DNR problem, two main groups of approaches are established: 1) mathematical (or exact) techniques and 2) heuristic and meta-heuristic techniques [11]. In the group of the exact techniques, some examples of this type of approach are Linear Programming (LP), Non-linear Programming (NLP), Quadratic Programming (QP) and Mixed Integer Conic Programming (MICP) [12]. However, this type of approach is hard to formulate and slow in convergence, and it gets worse when the problem has a lot of objectives [11], because of this, the heuristic and meta-heuristic techniques assume an important role in solving DNR problems. Some examples of this type of approach are based on Genetic Algorithm (GA) [1], [8], [13], [14], Invasive Weed Optimization (IWO) [12], Particle Swarm Optimization (PSO) [1], [11], among others.

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Moreover, DNR problems can also be classified as static or dynamic. In static reconfigurations, an improved fixed topology is defined at the planning stage, whereas in dynamic reconfigurations the grid configuration is changed in real time using remotely controlled switching (RCS), in an Active Network Management (ANM) scheme [7]. DSOs are responsible for changing the configuration of the network. Traditionally, they rely on a static "Optimal Configuration", defined at the planning stage. This configuration maintains proper grid operation under steady-state conditions and is only altered under adverse conditions. However, maintaining a static configuration under the fluctuations introduced by DERs has become challenging. The problem is that network configuration cannot change at any time, mainly due to the wear of the switch devices and operational costs derived from taking the maneuvers manually in the field, if that is the case, in distribution systems that are not fully automated. Thus, DSOs face the challenge of having the time and resources required to study all feasible configurations and consider the changing load and generation conditions.

Therefore, the use of more dynamic grid management strategies to ensure operational efficiency and reliability is needed to face the problems that DERs introduce and help the DSOs to maintain optimal grid operation. Several DNR under ANM schemes have been introduced in the literature to help the DSOs in their task [15]. However, these approaches are not fully deployed widely, mainly due to commercial and regulatory barriers [15], and operational costs that come from changing the network configuration at any time, which is not possible in real cases. Thus, other strategies need to be developed to deal with the fluctuations introduced by DERs penetration and load demand, while not making DSOs change the configuration several times.

In this work, a strategy to adopt different configurations according to the year´s season and different levels of PV penetration is employed. This is done by integrating a Mixed Integer Non-linear Programming (MINLP) problem with the NSGA-II, enabling the systematic identification of optimal seasonal configurations that outperform the traditional static approach. Furthermore, the results demonstrate that the optimal configurations are robust to different levels of PV penetration, providing DSOs with a practical tool to improve grid operational efficiency and reduce costs without the need for frequent interventions. Having this set of optimal configurations is a way to help the DSOs transition towards dynamic configuration management, without having to frequently intervene in the configuration of the system.

This paper is structured as follows. Section II presents the proposed methodology employed in this work. Section III presents the mathematical formulation of the problem. Section IV presents the cases of study, as well as the most relevant study results. Finally, in Section V the main conclusions drawn from this work are presented, as well as possible future works to be pursued.

II. METHODOLOGY

This work aims at finding the best configurations for each season of the year and for different levels of DG penetration. The complete process is described as follows, step by step:

1. Characterize different scenarios of generation and consumption. Each scenario will correspond to a different season of the year. To simplify the process of finding the best configurations, and reduce the computational burden of the optimization process, a typical day was chosen for each season. For each typical day, periods of 15 minutes were considered.
2. Define the different DG penetration (only PV production was considered in this work) scenarios.
3. Formulate mathematically the problem of optimization and calculate the objectives for the basis configuration, for each season of the year and for each percentage of DG penetration, made through running optimal power flows.
4. Use the Non-dominated Sorting Genetic Algorithm II (NSGA-II) to solve the optimization problem. This algorithm plotted the Pareto-front for each scenario of DG penetration, which is the set of configurations that present the best trade-off between both objectives. This process should be repeated at least 30 times, to ensure that the algorithm does not get stuck in non-optimal configurations and that all possible Pareto-fronts of solutions are considered.
5. Reunite all solutions from all Pareto-fronts of the 30 iterations and plot a final Pareto-front with all those solutions. Determine the dominated and non-dominated solutions and remove the dominated solutions from the set of best configurations, i.e. the solutions that presented the best trade-off between both objectives were maintained, and the others were removed. This is done for each percentage of DG penetration.
6. Finally, having the set of best configurations for each percentage of DG penetration, the repeated configurations are chosen and nominated as Optimal Configurations.
7. Calculate the objectives for all those configurations, for each season of the year and each percentage of DG penetration and compare the results with the results for the basis configuration.

III. MATHEMATICAL FORMULATION

The generalized mathematical formulation of the optimization problem, which is formulated as a MINLP problem, is provided in this section. The solution for the optimization problem is a radial and connected configuration that presents a lower value of active power losses and a higher value of the voltage index.

A. *Objective function*

The MINLP problem with the aim of minimization of active power losses and maximization of the voltage indexes is defined as follows:

1) *Active Power Losses*

$$P^{loss} = Min\left(\sum_{ij=1}^{N_{br}} \left|P_{ij} + P_{ji}\right|\right) \quad (1)$$

The first objective function aims at minimizing the active power losses. P^{loss} is the objective function to be minimized. P_{ij} is the active power flow from node i to j and P_{ji} is the active power flow from node j to i. N_{br} is the number of branches connected in the configuration that is being tested in the distribution system, for each instant of 15 minutes.

2) *Voltage Index*

$$VI = Max\big(minimum(Bus_{voltages})\big) \tag{2}$$

The second objective function aims at maximizing the voltage index (VI). VI, which is the objective function to be maximized, represents the minimum voltage value in all buses in each period of 15 minutes, and $Bus_{voltages}$ represent the voltages of all buses that form the configuration that is being tested in the distribution system, for each instant of 15 minutes.

B. *Constraints*

The optimization problem is subject to the following constraints:

1) *Constraint of Radiality*

$$numedges\ (G) = numnodes(G) - 1 \tag{3}$$

This constraint ensures that each configuration that is a possible solution to the network reconfiguration problem should be a radial topology. A radial topology ensures that there are no loops in the network configuration. G refers to the graph that is created when the network configuration is specified, and $numedges$ and $numnodes$ refer to the number of branches and buses of the network configuration, respectively.

2) *Constraint of Connectivity*

$$num(unique(bins)) = 1 \tag{4}$$

This constraint ensures that each configuration that is a possible solution to the network reconfiguration problem should be a connected topology. A connected topology ensures that there are no buses disconnected from the distribution system, making sure that all loads are energized. $bins$ refers to the connected buses of graph G.

3) *Active and Reactive Power Balance Constraints*

$$P_i - P_{d_i} = V_i \textstyle\sum_{j\in\mathcal{N}} V_j\big(G_{ij}\cos(\theta_i - \theta_j) + B_{ij}\sin(\theta_i - \theta_j)\big) \tag{5}$$

$$Q_i - Q_{d_i} = V_i \textstyle\sum_{j\in\mathcal{N}} V_j\big(G_{ij}\sin(\theta_i - \theta_j) - B_{ij}\cos(\theta_i - \theta_j)\big) \tag{6}$$

These constraints ensure power balance in the distribution system, meaning that the difference between the generated power and the load demand equals the power flowing through the network. Equation 5 ensures that the difference between the active power injected and the active power demand at bus i equals the sum of the power flows between bus i and all connected buses j.

Equation 6 ensures that the difference between the reactive power injected and the reactive power demand at bus i equals the sum of the power flows between bus i and all connected buses j. P_i and Q_i refer to the active and reactive power injected at bus i, respectively. P_{d_i} and Q_{d_i} refer to the active and reactive power demand at bus i, respectively. V_i and V_j are the voltage magnitudes at bus i and j, respectively. $\mathcal{N}$ is the set of all buses connected to bus i. $G_{ij} = \frac{R_{ij}}{Z_{ij}^2}$ and $B_{ij} = \frac{X_{ij}}{Z_{ij}^2}$ are the Conductance and Susceptance I of the line between buses i and j, respectively. θ_i and θ_j are the voltage angles at buses i and j, respectively.

4) *Voltage magnitude and Current Constraints*

$$V_i^{min} \le V_i \le V_i^{max},\ \forall i\ \in\ N_{bus} \tag{9}$$

$$I_{ij} \le \left|I_{ij}^{rated}\right|,\ \ \forall ij\ \in\ N_{br} \tag{10}$$

These constraints ensure that the voltage magnitudes at each bus stay within specified operational limits (9) and that the current flowing in the branches does not surpass the rated current in the branches (10). V_i is the voltage magnitude at bus i. V_i^{min} and V_i^{max} represent the lower and upper limits of the voltage magnitude of each bus. I_{ij} and I_{ij}^{rated} are the operating current and the rated current of the branch formed by buses i and j, respectively. N_{bus} and N_{br} are the number of buses and branches in the distribution system, respectively.

IV. RESULTS AND DISCUSSION

In this section, the functionality of the NSGA-II in solving the proposed MINLP formulation for distribution networks is studied. The standard IEEE 33 bus test distribution system is selected, and the obtained results are compared with the results from the basis configuration. This system is presented in Fig. 1 and has 33 nodes and 5 switches (33 to 37), a rated voltage of 12.66 kV, and total active and reactive power demands of 3.715 MW and 2.30 MVAr, respectively. The nodal active and reactive powers of this network are present in Table I.

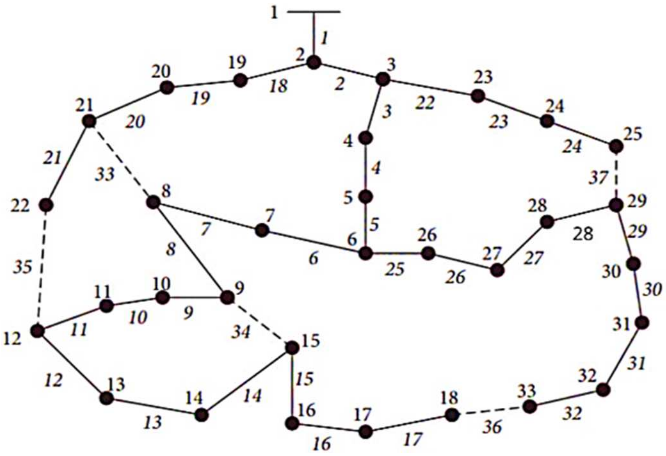

Figure 1. IEEE 33-bus distribution system - adapted from [16].

TABLE I. IEEE 33-BUS DISTRIBUTION SYSTEM NODAL ACTIVE AND REACTIVE POWERS

Node	P (kW)	Q (kVAr)	Node	P (kW)	Q (kVAr)
Bus 2	100	60	**Bus 18**	90	40
Bus 3	90	40	**Bus 19**	90	40
Bus 4	120	80	**Bus 20**	90	40
Bus 5	60	30	**Bus 21**	90	40
Bus 6	60	20	**Bus 22**	90	40
Bus 7	200	100	**Bus 23**	90	50
Bus 8	200	100	**Bus 24**	420	200
Bus 9	60	20	**Bus 25**	420	200
Bus 10	60	20	**Bus 26**	60	25
Bus 11	45	30	**Bus 27**	60	25
Bus 12	60	35	**Bus 28**	60	20
Bus 13	60	35	**Bus 29**	120	70
Bus 14	120	80	**Bus 30**	200	600
Bus 15	60	10	**Bus 31**	150	70
Bus 16	60	20	**Bus 32**	210	100
Bus 17	60	20	**Bus 33**	60	40

Node 1 is the slack bus, thus there are no active and reactive powers in that node. There are no DG units installed in any node of the system, and the DG penetration is distributed by each node of the system. The feeder is present in the slack bus, whose voltage magnitude is set to 1.02 p.u. The minimum and maximum acceptable ranges for node voltages are 0.9 and 1.1 p.u., respectively.

As stated in the methodology section, the NSGA-II algorithm was used to find the set of optimal configurations that presented lower values of active power losses and higher values of voltage indexes. All Pareto-fronts were plotted, and the repeated configurations were chosen to form a final Pareto-front.

From this final Pareto-front, the configurations that presented the best trade-off between the objectives were selected, and those configurations formed the set of Optimal Configurations, to be compared with the basis configuration.

In Table II this set of Optimal Configurations is presented. Each number inside the parenthesis corresponds to the number of the branch or switch that is open in the designated configuration.

TABLE II. SEASONAL CONFIGURATIONS OBTAINED THROUGH THE NSGA-II

Designation	Configuration
1	[7,9,14,32,37]
2	[7,9,14,28,36]
3	[7,9,14,36,37]
4	[9,14,28,32,33]

Five DG penetration scenarios were considered. Case A referred to 0 % of DG penetration, Case B referred to 30 % of DG penetration, Case C referred to 40 % of DG penetration, Case D referred to 50 % of DG penetration and Case E referred to 70 % of DG penetration.

A typical day was also chosen for each season of the year (Spring, Summer, Autumn, and Winter). Each configuration is tested for different scenarios of DG penetration and different seasons of the year, and the results obtained are compared with the results for the basis configuration.

The main results are highlighted in the following sections. Due to there being a lot of results, only the most relevant ones will be presented.

A. Active Power Losses analysis

To fully analyze the effect that different configurations and different levels of DG penetration in different seasons of the year have on the values of active power losses, the concept of Energy of Losses (EL) is employed. EL refers to the energy referring to each loss value, for each interval of 15 minutes.

To represent the energy losses in each season, for different percentages of DG penetration, the values of EL for each interval of 15 minutes, expressed as kW/h, were summed.

The results for Summer are represented in Table III. These results are highlighted since Summer is the season of the year with more hours of sun exposure, thus it is the season that is capable of better highlighting the effects of DG penetration (PV production) in the operation of the grid.

As can be seen, the values of EL are lower for all configurations obtained through the NSGA-II in comparison with the basis configuration, which means that the values of active power losses are also lower in those configurations, when compared with the results for the basis configuration.

In more detail, configurations 1 and 3 perform better than the other configurations across all scenarios of DG penetration, in the Summer, having loss reductions superior to 30% in comparison with the basis configuration. In addition, one can also conclude that the higher the percentage of DG penetration is, the lower the values of the losses and better grid operation.

The last remark is that the percentage of DG penetration does not influence the best-performing configurations, i.e., different levels of DG penetration do not change the configurations that perform better. With effect, configurations 1 and 3 are the best-performing configurations, despite the level of DG penetration.

TABLE III. EL VALUES - SUMMER

kW/h	Basis	1	2	3	4
Case A	930.99	647.28	665.30	650.14	685.21
Case B	600.33	419.12	430.71	420.96	443.56
Case C	524.70	366.48	376.60	368.08	387.83
Case D	465.62	325.22	334.20	326.64	344.17
Case E	395.50	276.12	283.75	277.33	292.22

B. Voltage Indexes analysis

The effect that different configurations with different levels of DG penetration in different seasons of the year have on the Voltage Indexes was also analyzed. Because the results are too extensive, only Cases A and E in the Summer season will be shown, in Fig. 2 and Fig. 3, respectively.

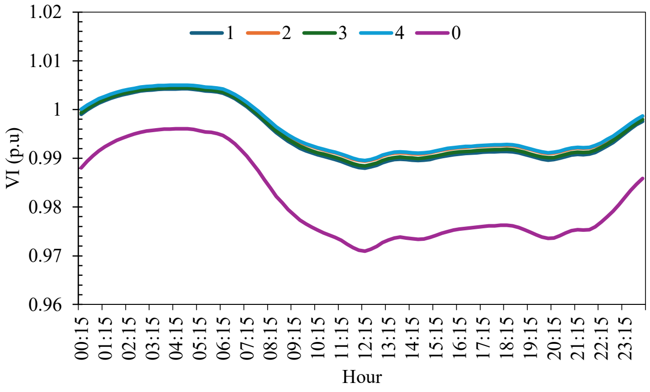

Figure 2. VI values in Summer - Case A.

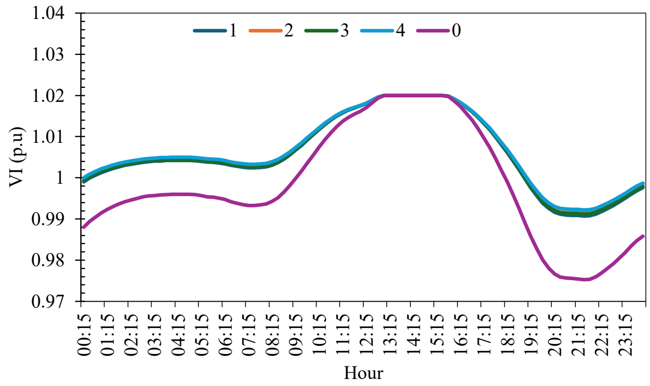

Figure 3. VI values in Summer - Case E.

As can be seen, different levels of DG penetration affect the VI results. With effect, it can be noted that for the same season of the year, the case where there exists a higher percentage of PV production, which is Case E, presents the better VI values for all configurations. In addition, it can also be seen that all the configurations that resulted from the NSGA-II present better VI than the basis configuration, in all periods of 15 minutes of the typical day.

V. CONCLUSIONS AND FUTURE WORK

In this paper, a strategy to help DSOs deal with the volatility introduced by the increasing penetration of DERs and load demand variations without making constant grid reconfigurations was employed. An NSGA-II algorithm was used to solve the proposed MINLP problem, by generating a set of configurations that formed a Pareto-front. These configurations were compared with the static basis configuration, for the values of active power losses and voltage indexes, for each season of the year and different percentages of PV production. The obtained results confirmed that the configurations generated outperformed the static basis configuration in terms of active power losses and voltage indexes, for all year's seasons and DG penetration scenarios. In more detail, configurations 1 and 3 were identified as having the best performance among all configurations. The level of DG penetration affected the magnitude of energy losses and voltage indexes, but it did not alter the generated configurations. In summary, this work demonstrated that adopting a seasonal grid reconfiguration strategy can help the DSOs achieve better grid operation, with reduced energy losses and better voltage profiles. In addition, since there is no need for constant grid reconfiguration because the seasonal configurations present robust behaviors in all scenarios of PV production, the operational efficiency is also increased, since there are minimal switching requirements with fewer costs associated. That way, DSOs can achieve significant performance gains with a limited set of configurations, reducing the cost and complexity of dynamic configuration management. This study can be extended in the following areas: a) Expand the analysis to include other DERs. b) Study the impact that the flexibility of the consumption patterns has on the grid. c) Use other algorithms to solve the MINLP problem and compare the results with the results of the NSGA-II. d) Develop a methodology that is capable of evaluating hundreds of feeders simultaneously.

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