BEHAVIOUR ANALYSIS OF AN OPERATIONAL PLANNING TOOL FACING ACTIVATION PROBABILITIES, FOR NEAR OPTIMAL OPERATION OF SMART GRIDS

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ABSTRACT

The dispatch down of renewable generation, as well as the combination of user controllable devices and network operation of grid components are flexibilities which are available in the distribution networks. Despite their added value for the system, their optimal control might bring more uncertainty in the operation of the network. In this paper, the authors evaluate the behavior performance of an operational planning tool that coordinates the flexibility activation planning, by introducing an activation probability for every flexibilities. An IEEE distribution network with distributed generation sources was used as base scenario for evaluation. A correlation between the probability of activation for load and generation flexibilities and the global result provided by the operation planning tool was observed. With the results gathered, the uncertainty's impact was analysed and some applications of the methods for futures works are proposed.

INTRODUCTION

The integration of renewable generation and the mitigation of its impacts are nowadays concerns. The management of Distributed Energy Resources (DERs) requires clever systems, which should be able to tolerate and handle uncertainties introduced by this type of resources. The development of new information and communication technologies provides new alternatives for the operation of distribution networks, by offering real-time communication, automatized grid operation and deployment of devices with decision making capabilities. The introduction of new technologies, within the distribution networks, can answer to the distribution network needs, allowing more automation and a better performance of the grid. In fact, a smart network should be able to handle constrained conditions introduced by todays Distributed Generation (DG) penetration.

Within this article the authors explore the implication of considered uncertainties in the activation of load and generation flexibilities. At first, a short overview of smart grids, flexibilities, uncertainties and reliability analysis is introduced. Then, a description of the uncertainty evaluations is detailed, an analysis of its impact is developed and finally some propositions for the future use of this indicator are proposed.

SMART GRIDS DEPLOYMENT

The Smart Grids (SG) are architectures which are summarized as digital energy networks that can actively enable and integrate local and aggregated user actions, automatically control energy flows, and adjust flexible energy supply and demand accordingly, guaranteeing a more reliable supply of electricity in a cost and resource efficient way.

In particular, this type of concepts can cost-efficiently integrate the behavior and actions of all users connected to this architecture. Some advantages of these energy networks are: low losses, high levels of quality and security of supply, and safety operation [1]. A cost-efficiently integration implies solutions that optimize the use of available resources in the distribution networks.

Flexibility within Smart Grids operation

The actors involved in the operation of a SG are the energy suppliers, the grid operator, the consumers or anyone that could consume or supply energy or capacity reserves. In a SG, some actors should be able to provide specific services that could help the grid under constrained conditions. These services will be served by the active operation of smart components from the actors. These services can be defined as flexibility. In a holistic sense, the flexibility can be understood as a modification of the generation injection and/or consumption patterns in reaction to an external signal (price signal or contractual activation) in order to provide a service within the energy network. The alteration in the consumption or generation patterns can provides one major asset: the reduction of energy losses while mitigating the technical constraints [2] [3].

The flexibility activations within the SG should not be seen as isolated operations. In fact, its deliveries can be designed as part of a package of solutions meant to optimize the distribution networks.

It is possible to mention that it exists other types of solutions proposed to adjust the network to new conditions, such as, for instance: distribution lines reinforcement, inclusion of high efficiency transformers, and voltage level variation [4] [5].

Within the scope of this paper, the available flexibilities within the smart grids were categorized in three groups; the Figure 1 is representing some of them, and the next terminology was defined to simplify the description along the article:

- **Supplier**. Dispatch down of renewable generation such as solar or wind production; the flexibility operation regulates a given generation unit during a period of time. Usually this operation is linked with a decision from the owner related to the energy market.
- **Network**. Services delivered by the distribution network operator; the services are executed by some active components in the network such as: capacitor bank, or On-Line Tap Changer (OLTC).
- **Customer**. Active response from the end user, or an actor on behalf of a group of end users (like aggregators). Their action could consist on actively alter their consumption and receive rewards for this service.

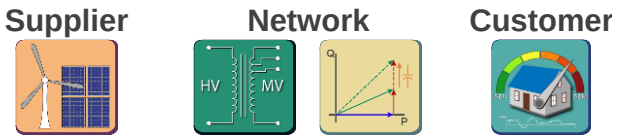

Figure 1. Considered flexibilities

Presentation of a dedicated algorithm for SG operation at Medium Voltage level

Most of Medium Voltage (MV) distribution networks are operated in radial configuration. From the substations, all the nodes are energized through MV feeders. Since the introduction of the renewable sources, the DG units are either connected to low voltage node or distributed along the MV network. An algorithm for the operation of flexibility offers in case of constrained situations can be defined, which means, to find the best combination of flexibilities to solve given constrained conditions. This algorithm should be capable to compute a solution within a constrained time of minutes and this could be used as an operational planning tool that guarantees a cost-efficient operation of the network.

An algorithm developed for MV network management within the European DREAM project was used during this work [6]. The project aims for the establishment of the bases for the novel heterarchical management of complex electrical power grids at the distribution level. The project takes advantage of: renewable resources penetration, novel techniques for operation of distribution networks and deployment of new ICT technologies [1]. A brief description of the MV algorithm is developed next; however, more details of the method can be found in [7].

The MV algorithm models the distribution network operation optimization through a cost function, from which, the penetration of SG solutions are considered.

$$\min f = \alpha_L P_L(x_i) + \sum_{i=1}^{nf} \alpha_i \, x_i \qquad (1)$$

Where
α_L: Cost of the losses within the distribution network.
α_i: Cost of the flexibility activation.
P_L: Total losses in the distribution network.
nf: Total number of flexibilities available.
x_i: Binary variable for the ith flexibility activation.

$$V_i^{min} \leq V_i \leq V_i^{max} \quad \forall i \in [1, n] \qquad (2)$$

$$I_j \leq I_j^{max} \quad \forall j \in [1, m] \qquad (3)$$

The expression (1) represents the objective function, it looks forward to minimize the cost of the activated flexibilities, guaranteeing the acceptable operation of the network. Expressions (2) and (3) are the constraints of the optimization problem, and are defining voltage and current limitations for each node. Where V_i and I_j are the voltage at the node i and the current in the line j respectively, n is the number of nodes and m is the number of lines.

Once the objective function is solved, a control order is corresponding to each considered flexibility offer. The obtained solution corresponds to a combination of flexibility activations that guarantee that the network fulfills the technical constraints of the network and minimizes the network losses. In short, the expected outputs of the optimization problem correspond to:

- The selection of OLTC positions
- The selection of one tap for every capacitor bank.
- The arrangement of activation of the available customer and supplier flexibility offers.

In fact, the solution of this problem cannot be easily found since it has discrete variables and the state variables of the system are subject to nonlinear constraints. In fact, this problem corresponds to a non-linear and non-convex optimization problem. Optimization strategies such as quadratic programing or non-linear programing cannot provide precise solution for this type of problem. Therefore, a method which uses non-conventional techniques is needed in order to obtain a good solution in a feasible time. In addition, the

complexity of the problem increases in an exponential manner with a small increase in the number of variables introduced.

As a result of the NP difficult problem, a genetic algorithm was selected to solve this problem [8]. It corresponds to one of the different propositions of meta-heuristic approaches used to solve optimization problems having the characteristics described in the previous paragraph.

Uncertainties during the smart grid operation

The flexibilities exploitation is build up with the operation of multiple infrastructures. Communication and electrical devices work together to deliver the most suitable configuration. In addition, the operation of renewable resources may rely on weather conditions. This framework brings uncertainty that may affect the delivery and the consumption of power, causing instability in the operation of the distribution networks. Therefore, a risk for non-delivery of flexibility should be considered. Some elements that can provide uncertainty in the flexibilities' delivery are:

- Malfunctioning of control devices;
- Loss of communications;
- Forecast error;
- Vulnerability to cyber attacks;
- High latency in communications;
- Operation in parallel to contingency situation;
- Change of the player's offer due to market prices.

Then, one can think that every algorithms which intend to manage flexibilities in distribution networks should be able to assess the impact of the uncertainty directly related to the flexibilities activation.

RELIABILITY OF THE SMART GRIDS OPERATION

The work developed aims at evaluating the robustness performance of a MV optimization algorithm. The algorithm uses a meta-heuristic approach to coordinate the flexibility activation in order to handle constraints in a distribution network. The robustness of an algorithm can be evaluated by checking the suitability of the solution, when the inputs are facing some uncertainties.

Method proposed

An analysis of the uncertainty within the inputs in a MV optimization algorithm is develop. The analysis can be done by building either a deterministic or stochastic method. While deterministic methods are capable to provide reliable results, they are less efficient in time when the number of variables increases. On the other hand, probabilistic methods are providing results with a margin of error, but are well suitable for models with several inputs. The probabilistic methods have been the best strategy until now to solve uncertainty in non-linear models [9].

If a deterministic method wants to be implement, some fixed inputs will be chose. When inputs deviations are introduced in a model, the analysis normally follows the worst case principle [5], which consists in choosing the worst and the best scenario for the inputs, executing evaluations, gathering results and concluding about the model. However, the worst case principle used as an evaluation technique for uncertainties will not provide a conclusion that could be generalized for all inputs.

The work of [10] provides some extra disadvantages concerning to deterministic methods. First, it might be difficulty to evaluate the worst and best scenario exists for each input of the whole variables. Second, all variables might not be at their best or worst levels at the same time in a real scenario [10]. Lastly, an increase in the scenario's complexity is leading to an increase of difficulty for processing the data. On the contrary, probabilistic methods can easily handle the disadvantages of deterministic methods. By evaluating methodically the whole range of uncertainties within the inputs in a model, is build up a statistical representation of the expected results and with it, generate a complete range of uncertainty evaluation from a model. Therefore, a stochastic method was chose for the analysis of the MV optimization algorithm.

Monte Carlo simulation

The Monte Carlo simulation is a computational technique based on an iteratively evaluation of a model, using arrangements of pseudo-random numbers as inputs and statistical analysis of the results obtained. This method operates as a random experiment, in the sense that the final solution cannot be known in advance. Monte Carlo simulation represents a methodical way to do a what-if analysis [5]. Its importance emerges from the ability to provide an analysis of models under uncertainties in their inputs. A statistical distribution of the output is obtained and it can describe the performance of a model within uncertainty in its inputs.

An uncertainty variable in the reliability of the flexibility activation for customers and suppliers flexibilities was defined. By contrast, the operation of the network flexibilities was considered as fully reliable.

SIMULATIONS & RESULTS

In order to assess the impact of uncertainty in the operation of the MV algorithm, a Monte Carlo method was developed; then the evaluation of the algorithm was

done in an iterative manner. A fixed probability of activation (P_{act}) was define for all flexibilities. For one iteration the next steps were follow: First, an activation or deactivation instruction was set for each flexibility, it was done by a Bernoulli distribution, using P_{act} for each flexibility. Second, the selected flexibilities were introduced as input in the MV optimization algorithm. Finally, the MV algorithm calculate the objective cost and then the iteration was repeated. The simulation stops once a define number of iterations were reached –such as it does not exist any statistical variation in the response–. All the objective cost solutions found on each iteration were collected and then analysed by using histograms.

The IEEE 33 nodes distribution network [11] was used for the Monte Carlo simulation of the MV algorithm (Figure 2). Two distributed generators (at nodes 9 and 33) and one capacitor bank (at node 4) are connected to the network. This network was already analyzed by the authors of [12], where they assessed an optimal reconfiguration algorithm. Concerning the present article, the optimal configuration of this distribution network is selected.

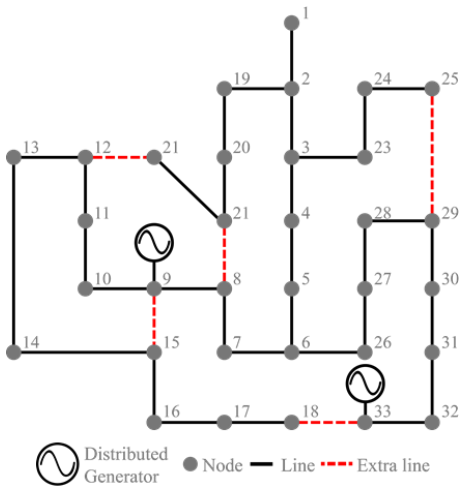

Figure 2. IEEE 33 nodes distribution

RESULTS AND DISCUSSION

Three different values for P_{act} were defined:

$$P_{act} = 0.1; 0.5; 0.9 \quad (4)$$

For each iteration, the objective cost solution was gathered and a histogram was developed. The results displayed on the Figure 3 represent the cumulative behavior of the algorithm's response for a defined P_{act}. The cumulative representation collects all the objective cost solutions of 2000 iterations, which have been divided and counted to form the different groups of bins displayed.

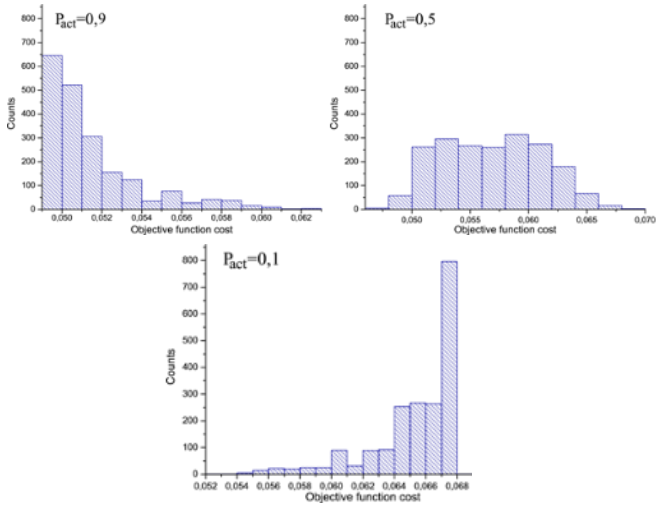

Figure 3. Objective function distribution per probability of flexibility activation

In the scenario with the highest probability of correct activation ($P_{act} = 0.9$), the most common solutions of the algorithm tends to decrease the values of the objective cost, which corresponds to the optimal and near optimal results. For the scenario with half of the probability of activation ($P_{act} = 0.5$), the algorithm provides less good solutions. Its result follow the behavior of a uniform distribution. Finally, in the last scenario, with the lowest probability of activation ($P_{act} = 0.1$), the algorithm provides solutions that are considerably distant from the optimum. Nevertheless, the group of solutions with lower P_{act} still guarantee the good operation of the distribution network by fulfilling the technical constraints.

In short, a correlation between the distribution of the results with regards to the objective cost and the probability of activation is observed. A direct relation between the degradation of the solution and the reduction of the probability of flexibility's activation is the behavior illustrated in the histograms in the Figure 3. In addition, this metric highlights the interdependencies existing among the electrical and communicational infrastructures. This study allows assessing the robustness of the MV algorithm by a statistical approach, and provides deterministic results when the model itself is non-deterministic.

CONCLUSION

The introduction of uncertainties in the flexibility activation has a direct impact on the successful operation of MV algorithms in the distribution network. The quality of the service can be reduced since the MV algorithm does not provide solutions close to the optimal.

FURTHER WORKS

The uncertainty analysis developed was conducted with several assumptions. Re-analyzing these assumptions can lead to a better comprehension of the reality and increase the quality of the developed study. Some of the assumptions that can be modified for futures works are:

Heterogeneous probability of activation

During this work, the same activation probability for each customer and supplier flexibility was assumed. However, the uncertainty on the activation of the flexibilities relies on several factors. Each factor does not has the same impact on each flexibility. Hence, it can be thought that every single flexibility has its own probability of activation. Moreover, each of them can be studied on regard to the network characteristics, the amount of required devices connected for its operation, and so forth.

A simplified statistical model for risk analysis

The distribution of the objective cost obtained for each probability of activation could be built with a binomial distribution probability. An extension of the work developed could study the difference and similarities between the optimization function and a binomial distribution. In fact, the MV algorithm can be studied by developing some assumptions on the flexibilities available, such as: failure probability independency per flexibility, variation in penalty cost, variation in activation cost, etc. A model like this could provide several analyses for smart grids evaluation. Among them: an analysis for the flexibility's risk dissemination at the distribution network, a tool to assess the quality of service in distribution network with a penetration of automation system, and also, the Distribution Management Systems could integrate a reliability indicator for control actions. In such way the system could choose to operate in a technically-economical or in a secure condition.

Robust optimization modeling

The aim for optimization techniques consists in providing solutions that maximize or minimize the objective function. Under real life conditions, the solutions provided by operational planning tools should remain truthful. To achieve this, some models capable to include the uncertainty within the parameters in the problem definition are needed. The target of robust optimization is to select the best solution that remains feasible for any realization of the uncertain parameters in the uncertainty set [13]. This work provides the basis to implement a robust optimization modeling for operational planning tools within SG. A redefinition of the objective function could be made by including the uncertainty in the problem's formulation and then taking advantage of the robust optimization technique to provide solutions that can fit better in reality.

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