CALCULATION OF NETWORK SECURITY MANAGEMENT (NSM) INTENSITY IN THE DISTRIBUTION SYSTEM

Chris Oliver HEYDE
Otto-von-Guericke University
Magdeburg – Germany
Chris.heyde@et.uni-magdeburg.de

Zbigniew A. STYCZYNSKI
Otto-von-Guericke University
Magdeburg – Germany
sty@et.uni-magdeburg.de

ABSTRACT

In this paper the calculation of the intensity of network security management actions by the network operator on distributed generators is discussed. Stochastic simulations in the form of Monte-Carlo simulations are employed. In order to have enough input data for the simulation, synthetic time series of the stochastic input variables must be generated in advance, using adequate models. Possible results of the approach are presented.

INTRODUCTION

The recent strong increase of distributed generation, especially wind power generation, in some regions of Germany, can produce bottleneck situations during times of strong wind and low load [1]. In such situations a distribution network extension or the use of generation response (GR) are required for the secure operation of the distribution system up to 110kV. The extension is quite expensive and time consuming, so some network operators have installed a Network Security Management System (NSM) to control the generation response in their distribution system.

The NSM limits the output power of groups of distributed generators in cases of network parameter violations like exceeding of line current limits caused by too much generation. Currently, there are two principles realising the NSM in Germany. The first is called the solidarity principle (all generating units are treated the same) and the latter is called the "first-in-last-out" principle (units are treated depending on their date of commissioning). Both principles can easily be simulated by this approach.

In order to consider all the stochastic input variables like wind power production, solar power production and load behaviour, which influence the application of the NSM, Monte-Carlo simulation is employed. Component outages will not be included in this first study. Because Monte-Carlo simulation needs a large amount of input which is not available as measured data, the stochastic behaviour has to be simulated with proper models. The following time step simulations are performed to simulate the network structure, the NSM principles and the network parameter limitations. In section 2 of this paper the stochastic models are introduced which are applied to generate synthetic input data for the Monte-Carlo simulation. Section 3 describes the time step simulation part of the study and section 4 represents possible results and their application to decision making in electrical networks. In section 5 conclusions are drawn and an outlook is given.

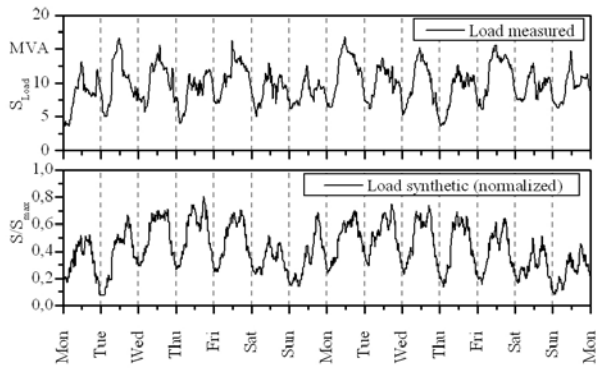

Figure 1. Example of measured load and synthetically reproduced time series for two weeks.

STOCHASTIC MODELS OF GENERATORS AND LOADS

Because of a lack of long term measurement data and because future developments are under investigation, the stochastic variables have to be modelled and their behaviour needs to be simulated. Therefore, a limited amount of measured data provided by two German distribution network operators was analysed [2],[3],[4]. The provided data is given as time series of active, reactive power and the voltage at several substations. From this data the two main stochastic variables, load and wind power production, can be investigated. Because they follow different stochastic processes, the different procedures are explained in the following subsections. Additionally, the models of solar power production and combined heat and power (CHP) are explained in the following sections.

Power profile of load

At first the data from substations with mostly energy consumers connected to it was selected. Then, the time series was normalized with the peak load measured at this substation. The procedure of filtering the statistical load characteristics is very similar to the procedure of giving synthetic load profiles for verification of energy costs in the field of energy trading. From the measurements, the hourly average values and the standard deviation of consumed apparent power for three periods of the year were calculated. In addition, workdays and weekends or holidays were distinguished. This gives six different daily profiles for one year including the average values and their standard

deviations.
To reproduce any number of new synthetic time series, an autoregressive process of 1st order was fed with these statistic daily profiles and random numbers. These time series now represent a mix of different customers because there were no differential measurements that would allow for statements about commercial, industrial, residential or agricultural load behaviour. The results are shown in Figure 1.

Power profile from wind generator

The infeed of wind power follows a different stochastic process than the demand. Here, the Markov process was found to be the most satisfying one. Therefore, from measured data at substations with only wind generators connected, the so called transitions probability matrix, also known as Markov matrix, is calculated [5]. Here, the year is also divided into three parts, summer winter and transition time for which a separate matrix is calculated. The measurements were also normalized at first with the installed capacity of wind power. Afterwards, the normalized data was separated into ten intervals, which represent the states S of the Markov process. The Markov matrix is derived from the transitions number matrix calculated as follows:

$$r_{ij} = \begin{cases} r_{ij}+1 & \text{if } S(t\text{-}1) = S_i \text{ and } S(t) = S_j \\ r_{ij} & \text{else} \end{cases} \qquad \text{Eq. 1}$$

$$r_{ii} = \begin{cases} r_{ii}+1 & \text{if } S(t\text{-}1) = S(t) = S_i \\ r_{ii} & \text{else} \end{cases} \qquad \text{Eq. 2}$$

With r_{ij} being the number of transitions between state S_i and S_j and r_{ii} being the number of cases when no transition has taken place.
From this the Markov matrix M can be derived:

$$M(i,j) = p_{ij} = \frac{r_{ij}}{\sum_{j=1}^{n} r_{ij}} \qquad \text{Eq. 3}$$

With the properties:

$$M(i,j) = [p_{ij}],\ 0 \le p_{ij} \le 1,\ \sum_i p_{ij} = 1 \qquad \text{Eq. 4}$$

To reproduce synthetic time series for the Monte-Carlo simulation two random numbers are generated for each time step. The first is to generate the transitions from one state to the other, following the probabilities in the Markov matrix. The latter is to put an equally distributed noise with the width of ±5% of the rated power to ensure that the 10%-interval is filled out with values.

Power profile from photovoltaic

Photovoltaic (PV) should only be considered in such studies, if there is a notable amount of installed power. Modelling the profiles of power production with PV is very similar to the modelling of load profiles. Here, measurements from one PV power plant were analysed to derive the hourly average values, their standard deviations and the autocorrelations for three sections of the year. Subsequently, a random number generator and a 1st order autoregressive process are applied to reproduce power profiles from PV power plants for any period of time.

Power profile CHP and conventional units

For this task, all CHP, bio gas and conventional power units are modelled as constant power producing units.

TIME STEP SIMULATION

Since all the analysed stochastic processes are time dependent (day-night load curve, seasonal weather changes, NSM principles etc.) the Monte-Carlo simulation has to be performed sequentially. This means, that the simulation uses input and produces output in a chronological order.

Modelling the network structure

Two different 110kV distribution networks were under investigation, one large 33 node network and one smaller 6 node network. When modelling the network, two aspects have to be taken into account: firstly, the geographical structure and secondly, the electrical structure.

Geographical structure of the network

If the distance between different substations is greater than 10 km, then correlations, especially between neighbouring wind farms, have to be considered. In each synthetic time series of wind power production the correlation of all individual wind turbines is already included because the transitions matrix is derived from data of a whole wind farm. To model the distance between different wind farms, a certain correlation factor has to be generated. Therefore, first the correlation factor needs to be calculated from measured data of two neighbouring wind farms. Thereafter, the dependence of the correlation factor from the distance is considered to be linear. To generate the correlation factor between the wind farms, one wind farm, which is located in the middle of the network, is set to be the reference wind farm. The time series of all other wind farms are generated by shifting the reference time series randomly a few steps backwards or forwards. To realize this, shifting operators are introduced that have different probabilities for different distances. These shifting operators have to be chosen in such a way that the average correlation factor after a sufficiently high number of trials is close to the calculated one from the linear function. The probabilities of the shifting operators used are shown in Table 1. Figure 2 shows how the aimed average correlation factor of 0,943 is almost reached after a number of trials.
The geographical locations of load points and of PV power plants have not been considered. Here the correlation factor equals 1.

Table 1. Shifting operators for generating correlation factor of neighbouring wind farms.

Distance [km] \ Shifted time steps	-3	-2	-1	0	1	2	3	Aimed correlation
0	0	0	0	100	0	0	0	1
0-10	0	5	5	80	5	5	0	0,988
10-20	3	2	10	70	10	2	3	0,965
20-30	5	10	20	30	20	10	5	0,943
30-40	12,5	15	15	15	15	15	12,5	0,920
40-50	22	22	5	2	5	22	22	0,897
50-60	28	12	9	2	9	12	28	0,875

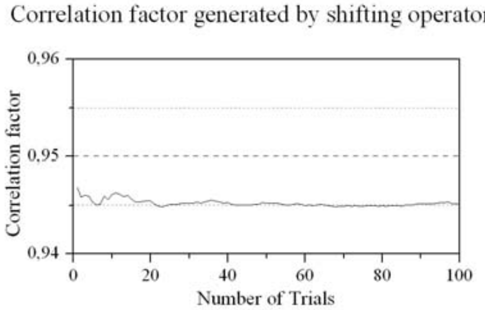

Figure 2. Average correlation factor for the distance 20-30 km after one and up to one hundred trials.

Electrical structure of the network

To consider the electrical structure of the network, a load flow calculation must be performed. This way all network components with their critical parameters can be observed, and power losses can also be considered. If the location of the bottleneck is known, simplifications can be made. For this example a case was chosen where the bottleneck is on the connection line to the superior network. Hence the network under investigation was treated as one accumulated substation. The current in this connection line was calculated from the accumulated apparent power and the rated voltage.

Modelling the NSM procedure

Usually the network operators form groups of generating units that are in some way related or responsible for a certain bottleneck. These groups can also contain several subgroups, as in the case of the "first-in-last-out" NSM principle. The output power of each group or subgroup can be limited in three steps to either 60% (step 1), 30% (step 2) or 0% (step 3) of their rated power [6].

If a certain NSM criterion is most likely to be reached, an algorithm estimates the states that all of the considered generating units are in, using available online data. From this estimation the NSM step can be calculated which is required to clear the bottleneck situation. In this simulation the procedure is the same, also taking in to account, generating units that are not participating in the NSM for some reason (special contracts, early installation date). In addition, a minimum duration of any limitation is one hour to avoid permanent switching. To clear the limitation, the program continuously checks if the limitation can be cancelled or lowered.

Recording the results

During time step simulation the results are saved in a separate file. For every limitation by the NSM the consecutive number, the number of time steps it lasted, the limitation step and the possible output power of the limited unit in case of no limitation is written in this file. At the end of one trial (one simulated year), the number, the average duration and the average limitation step of the limitations are calculated. In addition the energy that can not be produced due to the NSM can be calculated. In case of different groups, the results for each group are saved separately.

RESULTS

The results of the simulation procedure allow for determining the impact of the NSM on distributed generators. The nature of stochastic simulation is that it never produces exactly the same output. This is why a sufficiently high number of trials have to be simulated. In this case the number of 100 trials (100 simulated years) has been found to be enough. To simulate future development, considering an increase in distributed generation, the installed power is raised in defined steps. For each step 100 trials have to be simulated.

In the following diagrams the results are presented.

Figure 3 shows the average number of situations during one year in which the NSM had to be activated. Two different networks were studied with two different NSM principles. The bottleneck situations start after exceeding the network transfer capacity by 10% and by 30%, respectively. This clearly depends on the minimum load in the individual network. Except for this the two curves are almost parallel. The green lines in Figure 3 clarify the consequences of forming of groups by installation date. The earlier a generation unit is installed, the less it is affected by NSM limitations.

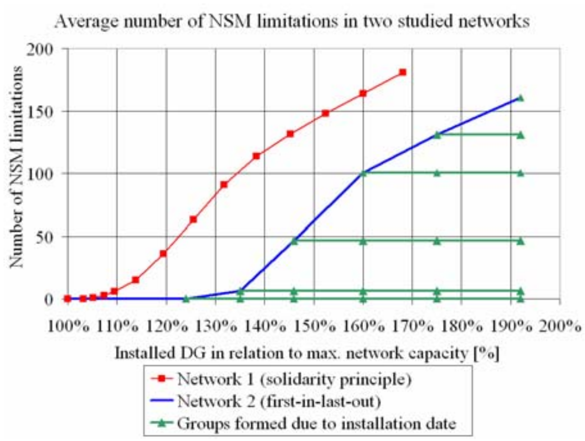

Figure 3. Average number of NSM limitations for two studied networks, one with solidarity and one with "first-in-last-out" principle. The latter with intensity on each group.

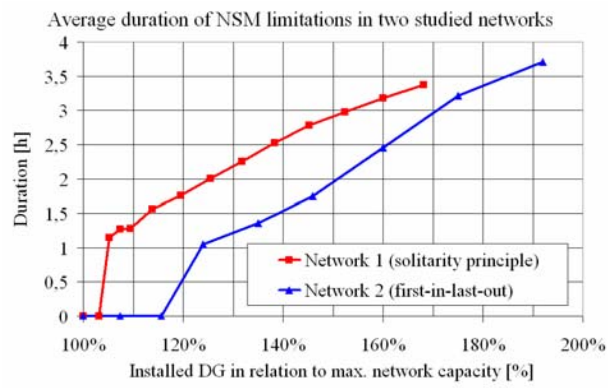

Figure 4. Average duration, in hours, of each NSM limitation in two studied networks; one with solidarity and one with "first-in-last-out" NSM principle.

Figure 4 shows the average duration of each NSM limitation in hours. One can clearly see the minimum limitation time of one hour. With increasing installed DG, the duration increases almost linearly.
By multiplying the average number and the average duration, one gets the total amount of time the DG units are exposed to NSM limitations (Figure 5). In Figure 5 the consequence of network extensions can also be seen. It makes clear, that NSM can be a good short term solution while network extensions are being planned and realized.
Figure 6 shows the portion of the energy $E_{limited}$ that can not be fed in the network due to NSM limitations. It is calculated by accumulating the difference of the possible output power of the DG and the limitation step in case of the NSM situation. This is put in to relation with the energy of some typical full load hours of each considered generation type E_{yield}.

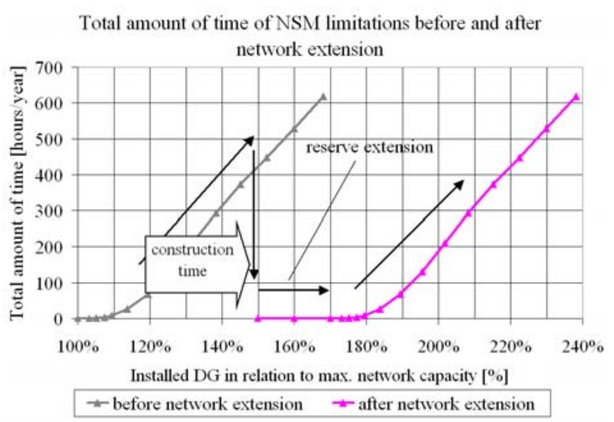

Figure 5 The consequences of a network extension considering the construction time and a reserve extension.

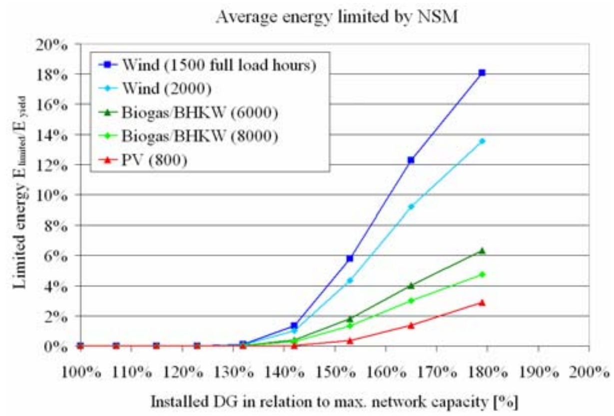

Figure 6. Portion of energy limited by the NSM, considering typical full load hours of each kind of generation unit.

CONCLUSIONS AND OUTLOOK

This simulation approach makes it possible to estimate the future behavior of individual distribution networks. Different mixtures of load and generation types and their stochastic characteristics can be considered. The network structure is geographically considered, and should also be electrically considered if the bottlenecks are located within the network structures and not on the borders. Also, the availability of network components can be taken into account, which would lead to a stochastically changing NSM criteria.

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