INFLUENCE OF WIND POWER PLANTS ON POWER SYSTEMS OPERATION

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Abstract— In recent years, renewable energy sources (RES) has increased all over the world, especially in Europe, and the changes brought by these sources have a significant impact on system performance and efficiency. Integrating RES to an electric power network offers many techno-economical benefits and in the same time necessitate advances in the operation, control and planning of electric networks. This paper focuses on the influence of the interconnecting of wind power plants on the electric network in terms of optimal power system operation. In this paper is proposed a k-means clustering based approach to identify the typical load profiles for wind farms in order to achieve the optimal power system operation on minimizing the power losses.

Keywords-wind power plant, optimal operation, typical load profiles, clustering techniques.

I. INTRODUCTION

The electricity industry restructuring, along with advances in small scale generation technologies, and a higher awareness of environmental issues are the key factors that have influenced the development of RES in the last period of time

[1]. The electrical network of the future should be flexible, efficient, reliable and security of supply and in the same time will allow two way flows of energy and real time communication capable of self healing and enabling fast restoration from supply disruption facilitate market operations and customer choice and information [2].

The growing integration of the renewable energy sources like solar power, wind power, or combined heat and power in the power network impacts a lot of interested parties: transmission and distribution companies, the owners and operators of the distributed generation sources, other end users of the power network, regulators and policy makers.

An increasing introduction of RES without any changes in the electrical networks will ensue in unacceptable levels of quality and reliability. Small distributed generation sources (DG) are located to the medium or low voltage distribution network, where traditionally only consumption has been connected. The penetration of large quantities of them will require improvements not only at the voltage level where the sources are located but also at higher voltage levels. The intermittent character of renewable energy production introduces new power quality phenomena, representatively at lower voltage levels [3]. Besides, this variation as well as the difficulty in estimating RES production impacts the operation of the power transmission networks. These are the principal reasons why the RES integration is a very attractive research subject and it will continue being of great interest.

The changes brought by RES have definitely an important impact on system efficiency and performance and necessitate enhancements in operation and planning of electrical system. In order to maximize the potential RES benefits in the future could be taken enforcement measures or upgrading actions for improving the system performance and reliability. The upgrading process will be done, taking into consideration the electricity delivery infrastructure that is divided into transmission and distribution system, [4].

The traditional planning process for expanding transmission system is based mainly on its needs on past and designed loading levels, which have traditionally been assessed of future demand. In the deregulated market, and in the case of using different renewable energy sources, transmission planners must respond to the necessities of power generators. Otherwise, planning to develop transmission system may now be established by the location and type of generation source, rather than by the necessities of the transmission system.

Around the world, wind and photovoltaic power are considered to have the largest potential in electricity production from renewable energy sources, [5].

Currently wind energy has the largest interest because Romania has the highest potential from the Southeast of Europe, and Southeast of Romania ranks on the second place across the entire continent. In the past 10 years more studies considered necessary and appropriate addressing some activities of reassessment of wind potential of Romania, through the use of appropriate tools and instruments (measuring equipment, appropriate software) from measured wind data stations belonging to the National Agency of Meteorology, [6]. In [7] is given an estimate of the theoretical potential of wind energy corresponding (approximately 14 GW of installed capacity). Annual energy of this potential is 0,023 TWh / year.

Because in the last years there is an increase of wind farms connected to the grid powers, the electrical companies need by studies and analysis for to evaluate the impact of these sources on the system. These activities are performed in order to ensure reliable operation of the system in presence of wind farms [7], [8].

There are many requirements, prescriptions and guidelines that to refer to technical information necessary for assessment

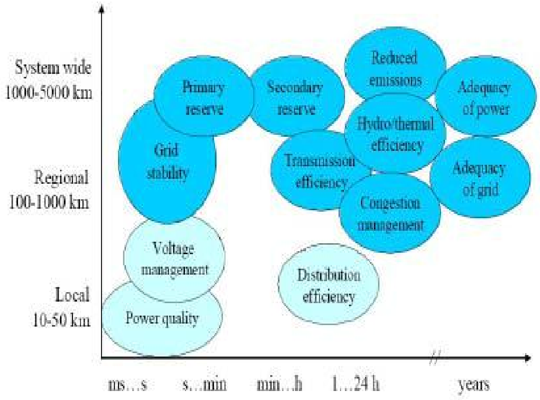

Figure 1. Influences of the wind sources connected to the power systems, [8]

The operation system of the wind turbine is conditioned by two parameters (speed wind - v and wind variations) . There are three operating states that can be differentiated, [9], [10]:

Standstill of the turbine – for v < vcut-in or v > vcut-out, where vcut-in and vcut-out represent cut-in and cut-out wind speeds .

Partial load – for vcut-in ≤ v ≤ vn, where vn is the rated wind speed.

Full load – for vn < v ≤ vcut-out. The value vcut-out is usually 25 m/s..

These three states represent characteristics P - v of the wind power plant. In order to study the influences of a wind sources on power system, it is needed to determine the patterns as accurately as possible. In the literature different techniques have been used for the classification and load profiling, but most of them were implemented to solve the problems from power systems. A review of the literature revealed two types of methods: statistical methods [11], [12] and methods based on artificial intelligence techniques fuzzy logic [13], [14], neural networks [15], data mining [16], clustering,

[17]-[19].

In the paper an approach able to identify the optimal power systems operation considering the typical load profiles for wind farms is presented. First of all, an algorithm based on k-means method was used to find the typical load profiles for wind farms using a wind power generated database. After that, with this approach it can be find the optimal power system operation in order to minimize the power losses.

II. DETERMINATION OF TYPICAL LOAD PROFILES FOR WIND POWER PLANTS

An approach based on clustering to determinate the wind power profiles for wind power farms from an electrical system is proposed. The K-means clustering algorithm used is used to classify operational profiles of wind power farms into coherent groups. By knowing these profiles, the operators can streamline the assessment of the demand.

The load profiling represents a different approach than the one based on metered demand. In this manner, for wind power farms from the electrical system are assigned a typical load profile. The shape of operational characteristic is influenced by the day (working or weekend) or season (spring, summer, autumn or winter). The operational characteristics of wind sources are in a very large number. This aspect create problems in analysis them. Thus, for an easy handling, they can be grouped in patterns, in function by the similarities between these. Every pattern will be characterized by a characteristic profile named typical load profile (TLP), [20], [21].

Each TLP is represented by a vector xi = {xih, h = 1,…, T} for i = 1, …, K, and the comprehensive set of TLPs is contained in the set P = {xi, i = 1, …, K}. The time scale along the day is partitioned into T time intervals of duration th , for h = 1,…, T. Hourly values are used in this paper to exemplify the application. The variables used in the calculations are assumed to be represented as constant (average) values within each time interval. The clustering process forms K patterns corresponding the wind power plants. Further, the typical load profiles are assigned to wind power farms.

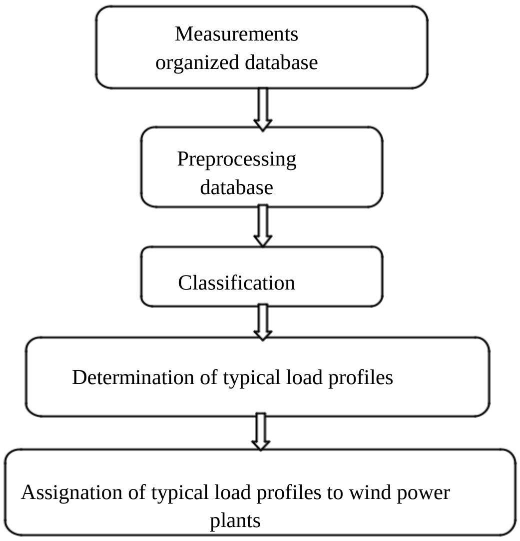

Figure 2. Flow-chart of the TPLs determination.

The proposed algorithm has the following steps, Fig. 2:

Step 1. Measurements: In this stage a database of operational characteristics is built.

Step 2. Data cleaning and pre-processing: A lot of technical aspects refer to communication problems, failure of equipment, etc., that can influenced negative the analysis need to be cleaned, pre-processed and reduced before the operational characteristics to be used in the clustering process.

Step 3. Classification : To realize this grouping, the K-means algorithm is used. Each operational characteristic is normalized. The normalization is made using the following relation:

$$z_h^{(j)} = \frac{x_h^{(j)}}{X^{(j)}}, \quad j = 1, \ldots, N,\ h = 1, \ldots, T \qquad (1)$$

where:
$z_h^{(j)}$ – the normalized value;
$x_h^{(j)}$ – the measured value;
$X^{(j)}$ – the normalizing factor over the surveyed period (energy over analized period);
N – number of wind power farms from electrical system.

Step 4. Determination of typical load profile for wind farms: In this step, a refining of normalized characteristics occurs so that the unrepresentative characteristics are eliminated. Further, the TLP for each pattern is obtained using an averaging process of the hourly values. TLPs obtained can characterize very well the operation mode of the wind power farms, regarding to the electrical energy consumption.

5. *Assignation*: Finally, for each pattern of wind power farms, a TLP can be assigned.

6.

III. OPTIMIZATION MODEL

objective of the planning formulation is to enhance the performance of the systems by minimize the active power losses. The main goal of the paper is to determine the optimal power system operation considering wind power sources in to an electrical network, minimizing the power losses. A mathematical expression of the problem is:

$$\min F(X) = \min P(U) \quad (2)$$

where X is a power flow solution which stores data about the location in the system and the power capacity of the generators as well as of loads; $P(U)$ represents the power losses that depend of vector U.

To minimize the power losses into a electrical network, was used relationship (6), where R_{ij} is the resistance in to branch ij, i=1...n, j=1...n, $i \neq j$, P_i and Q_i are the real and reactive power into a node i, U_n the nominal voltage and $N_{branches}$ the number of branches in the network:

$$F_1 = \sum^{N_{branches}} P = \sum^{N_{branches}} \frac{R_{ij} * (P_i^2 + Q_i^2)}{2} . \quad (3)$$

This item should compose with constraints to obtain the proper objective function. The main constraints in the process to determine the optimal power system operation with the proposed methodology are:

1. Voltage stability

where: $U_{i\min}$, $U_{i\max}$ – minimum, maximum allowable voltage level in the system at bus i; U_i – voltage level at bus i.

2. Branch thermal limits – the power over the branch ij, S_{ij} ,
must be less than the maximum limit admissible that can
support the line $S_{ij}^{\max}$.

$U_{i\ \min} \leq U_i \leq U_{i\ \max}$.(4)

Sij ≤ Sijmax . (5)

3. Generation limits - power generated by wind power plants is included between the maximum power allowed in bus i,

PDGi,max.

PDGi ≤ PDGi,max . (6)

4. Constraints for reactive power:

Qi min ≤ Qi ≤ Qi max . (7)

where: Qimin, Qimax - minimum, maximum allowable reactive power level in the system at bus i; Qi - reactive power level at bus i.

5. The power losses after installing wind power plants in electrical network should be less than power losses before installing it.

PwithDG ≤ PwithoutDG .(8)

IV. CASE STUDY

The proposed method was used for the optimal operation of a test electric network 220/110 kV with 10 nodes (3 nodes by 220 kV, and 7 nodes by 110 kV) and 12 branches (2, 220 kV electric lines; 7, 110 kV electric lines and 3, 220/110 kV power autotransformers), Fig. 3.

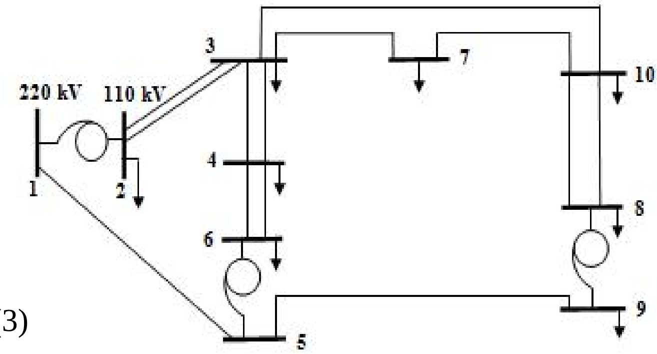

Figure 3. 220/110 kV test system.

In the test network a great potential based on wind energy was located in the region around the nodes 6 and 8. Thus, the wind power farm located in node 6 have a total installed capacity of 50 MW and the wind power farm placed in node 8, 25 MW.

In the case study a database described by generated power models, for the autumn season (3 months), corresponding to a group of wind power farms from the test electric network wasconsidered. Every generated power model is described by 24

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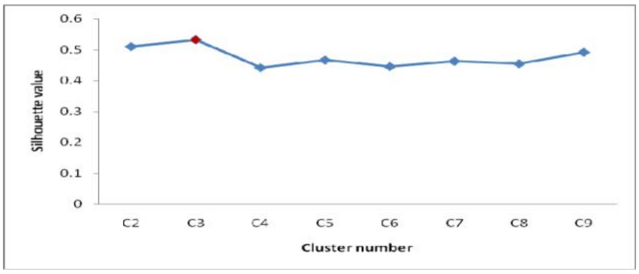
hourly points that depict the behavior of a wind power plant during a day.

The general information used in the clustering process concerns on generated power by the wind power plant, hour per hour for 3 months.
For determination of the optimal number of patterns, the algorithm presented in [21] was used. Thus, in the first step, the maximum number of patterns Kmax must be determined. The value of Kmax was calculated with relation Kmax = N , where N represents the total number of characteristics from database (N = 90).

In the second step, the k-means clustering method with values for K between 2 and Kmax is used.

In the step three, the quality of grouping is evaluated using the silhouette global (SG) coefficient, Fig. 4.



From Fig. 4, it can observe that optimum value for K is 3. For this value, in Fig. 5 is represented the forms (silhouettes) of patterns.

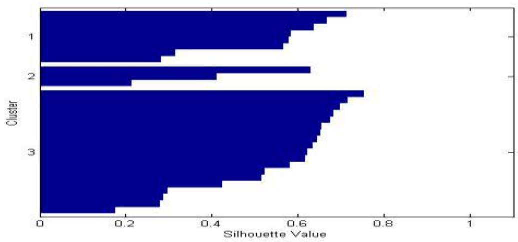


Figure 5. The forms (silhouettes) of patterns (case K = 3).
Each pattern is characterized by a TLP that was obtained by an averaging process of the hourly values.
The wind generated power characteristics for each pattern are presented in Figs. 6-8. TLPs of the wind power farms corresponding to three obtained patterns (WPP1, WPP2, and WPP3) are indicated in Figs. 9-11.

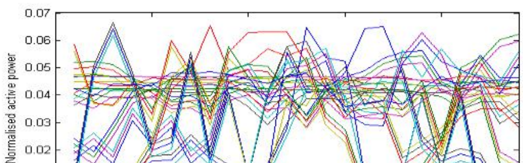


Figure 6. Generated power characteristics for WPP1pattern

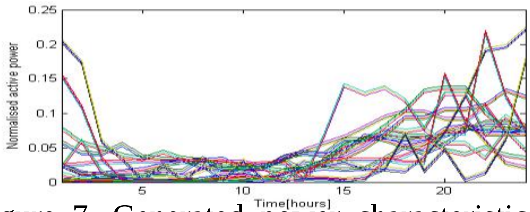


Figure 7. Generated power characteristics for WPP2 pattern

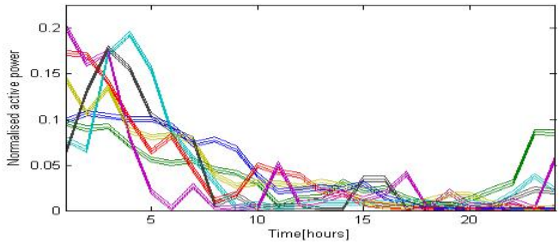


Figure 8. Generated power characteristics for WPP3 pattern

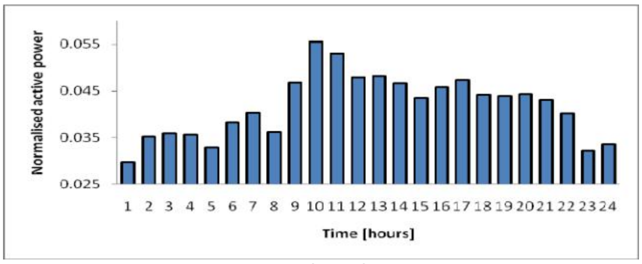


Figure 9. Typical load profile for WPP1 pattern

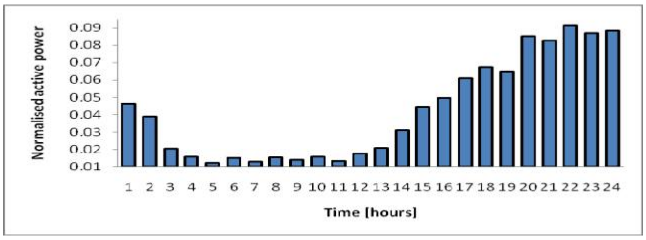


Figure 10. Typical load profile for WPP2 pattern

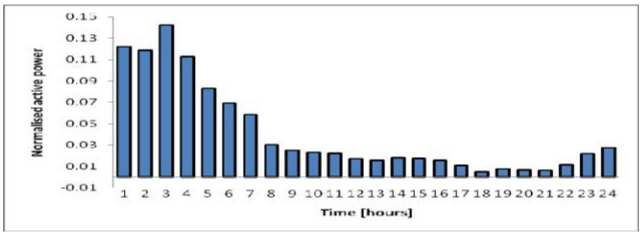


Figure 11. Typical load profile for WPP3 pattern

Further, considering these three TLPs are performed power flow calculations to analyze the evolution of the objective function. In this process the operating autotransformers plot was considered constant.

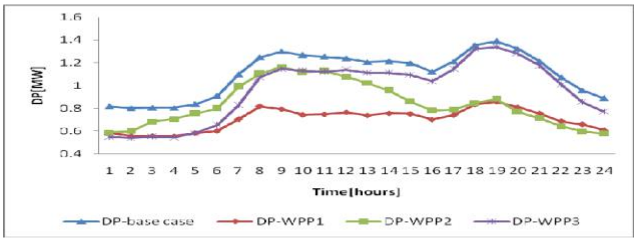


Figure 12. Objective function evolution in base case compared with cases WPP1, WPP2 and WPP3

Fig. 12 shows the evolutions of the objective function in the 220/110 kV test network in the initial case (without wind power plants), in comparison with the cases when wind energy is injected coresponding to the three typical load profiles WPP1,WPP2 and WPP3.

Analyzing the results, it can see that a classification of the wind operation characteristics is useful to view the optimal operation and planning of an electric power system, on minimizing the power losses. The typical load profile WPP1 corresponds to the best power system operation for the test network, taking into consideration that has a full load operation state all the day. The objective function values, at peak load, in the base case and in case WPP1 and the voltage values evolution in nodes with wind energy injection are presented in Table I.

TABLE I. OBJECTIVE FUNCTION AT PEAK LOAD VERSUS VOLTAGE VALUES IN NODES WITH WIND ENERGY INJECTION

Objective Function				Voltage Values [kV]	
	DP[MW]	DP[%]		Base case	Case WPP1
DP-base case	1.3882	0.7744	Node 6	116.189	116.825
DP-WPP1	0.8584	0.4803	Node 8	113.674	114.297

CONCLUSIONS

In this paper a clustering technique based approach was proposed for determination the TLPs using a database described by wind power operation models, for the autumn season (3 months), corresponding to a group of wind power plants from the test electric network. The TLPs resulted describes very well the operation states of the wind power farms. So, WPP1 profile is characteristic for the operation at full load and WPP2 and WPP3 correspond to partial load operation state.

The results obtained demonstrate that the proposed approach can be used with success in the optimal power system operation on minimizing the power losses and in the same time to improve the voltage magnitude into an electric network.

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