

Optimal Dispatch of Reactive Sources in Wind Farms

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Abstract— This paper suggests three different approaches for online reactive power dispatch in wind farms by using a new heuristic optimization algorithm called Mean-Variance Mapping Optimization (MVMO). Optimization for any given operating point will result in minimum losses but doesn't allow the consideration of the cost of on-load tap changer (OLTC) movements. To solve this problem the authors propose a predictive optimization where the objective is extended by the number of OLTC tap changes. Besides several time steps ahead are optimized simultaneously by using the information provided by a short term power forecast. In addition the authors suggest a method for incorporating the reactive power optimization into the wind farm control loop so that it can be used online to determine the optimal distribution of reactive power generation by each wind turbine. The proposed methods are demonstrated in a representative offshore wind farm.

Index Terms— Reactive power dispatch, offshore wind farms, Mean-Variance Mapping Optimization, heuristic optimization

I. INTRODUCTION

Transmission grid codes in many countries require wind farms to supply not only active power but also reactive power to the power grid. To achieve the reactive power requirement in an optimal manner, wind farm operators may consider performing reactive power optimization within their own facilities. According to the grid codes [1] the reactive power requirements are defined alternatively in terms of the power factor, the amount of reactive power supplied or the voltage at PCC.

The available reactive sources within the wind farm are shunt reactors connected to the submarine cables or directly to the busbars, the capacitance of the cables itself, additional capacitor banks if necessary and the wind turbines. Sometimes FACTS [2] devices such as SVC or STATCOM are also considered. Optimal utilization of the available Var sources along with the transformer on-load tap changer (OLTC) constitutes the optimal reactive power dispatch problem. It represents an optimal power flow task which minimizes the total power loss by maintaining the bus voltages and loadings of transmission devices in acceptable levels [3]. However, the stochastic nature of the wind speed poses a serious problem to

the reactive power management of wind farms. In contrast to traditional reactive power dispatch in transmission grids the update of optimal settings of reactive sources is required more frequently. As a result OLTC have to be more frequently regulated in order to maintain the voltage profiles within acceptable or optimal range. This increases the operation and maintenance cost of the transformers. Limiting the number of OLTC operations has been investigated in many OPF applications, such as [5]-[6].

In this paper the authors suggest a predictive control approach where actions are taken on the basis of a wind speed forecast for an interval of 30 minutes. The idea is to avoid short term OLTC tap changes by adapting the control to 30 minutes wind power expectation. To achieve this goal a short term forecast of the expected wind scenario for the considered time frame is required. To minimize the number of OLTC tap movement it is necessary to consider the corresponding costs in the optimization objective. As a result, the OLTC will only be considered either when constraint violation cannot be resolved by any other measure or the increase of losses exceeds the cost of OLTC tap activity over the considered period.

Optimization has been a key tool in power and energy systems for decades. Various techniques have emerged to handle different kinds of problems. These techniques can be broadly classified into exact and stochastic algorithms. Existing optimization software relies on the former group of techniques, such as linear programming [3] and interior point methods [4]. This is mainly due to uniqueness of the solution and fast computational speed. However, if the problem is deemed NP-hard or NP-complete, stochastic optimization algorithms (SOAs) become mandatory because of their ability to find at least quasi-optimal solutions with reasonable efforts. Moreover, SOAs are more suitable for some problems with no explicit cost function or with noisy environment [7].

Recently, several SOAs have been proposed in literature such as particle swarm optimization (PSO), ant colony optimization, genetic algorithms, evolutionary programming (EP), bacterial foraging algorithm, differential evolution and artificial immune systems. These algorithms have been successfully applied to various applications in power and energy sectors [9]. Although some efforts have been devoted to improving these techniques, not much investigation has been done to address the issues of violation of boundary conditions. To eliminate this problem, the authors developed a new stochastic optimization algorithm, namely mean-variance-mapping optimization (MVMO). The evident merit of MVMO is that a new offspring generated by a special

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mapping function in every update is always inside the respective bound. At the same time, diversification and intensification are well balanced in every stage of the search process. Based on the success gained in test problems for unconstrained optimization as shown in the previous work [9], the authors now present an application of MVMO to reactive power optimization of wind farms.

II. PROBLEM FORMULATION

The reactive power dispatch problem is an optimization task to manage the various var sources in a wind farm system so as to minimize the real power transmission losses, improve the voltage profile in the system and also minimize an uneconomical large number of tap changes of OLTC is formulated as a multi-objective function as shown in (1).

$$\text{minimize } \sum_{t=1}^T (w_1 OLTC_{\text{cost},t} + w_2 E_{L,t}) \quad (1)$$

where optimization is performed for a certain time horizon T . w_1 and w_2 are weight coefficients. $OLTC_{\text{cost}}$ is the total operational cost of the OLTC which is a function of the number of tap changes

$$OLTC_{\text{cost}} = \sum_{i=1}^{N_{Tr}} w_3 \sum_{t=1}^T |tap_{Tr,i}^t - tap_{Tr,i}^{t-1}| \quad (2)$$

The weighting factor w_3 corresponds to the cost for one tap change. E_L is the total energy loss calculated as shown below:

$$E_L = \sum_{k=1}^{N_l} P_k \cdot \Delta t \quad (3)$$

where P_k is the real power losses in line k , N_l is the total number of lines including cables within the wind farm and Δt sampling time. The line losses are calculated according to:

$$P_{k=(i,j)} = G_{ij} (V_i^2 + V_j^2 - 2V_i V_j \cos \delta_{ij}) \quad (4)$$

The system constraints include the TSO specified grid code [1] requirements as shown in Fig. 1. The wind farm must be able to operate at any point within the area in the diagram.

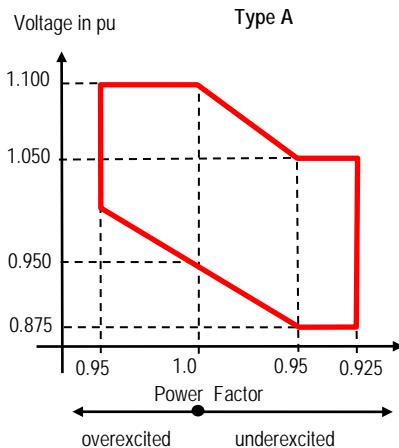


Fig. 1. Example for grid code requirement at PCC

Utilities can define the operating points required as power factor, reactive power or voltage reference at PCC. In this paper the reactive power definition accordance to (5) is used.

$$Q_{PCC} = Q_{\text{ref}} \quad (5)$$

Eq. (5) represents an equality constraint for the optimization. The other equality constraints are the power balance equations which include the active and reactive power balance equations for each load bus and the real power balance equations for each generator bus.

$$P_i - |V_i| \left| \sum_{j=1}^N |V_j Y_{ij}| \cos(\delta_{ij} - \theta_{ij}) \right| = 0 \quad \forall i \in N \quad (6)$$

$$Q_i - |V_i| \left| \sum_{j=1}^N |V_j Y_{ij}| \sin(\delta_{ij} - \theta_{ij}) \right| = 0 \quad \forall i \in N \quad (7)$$

where P_i and Q_i are the net active and reactive power injected at bus i , respectively; Y_{ij} is the admittance matrix corresponding to the i^{th} row j^{th} column and θ_{ij} is the difference in the voltage angle between the i^{th} and j^{th} buses. The system operating constraints constitute the inequality constraints on the dependent variables such as the voltage magnitude of the buses other than the PV buses and currents through the cables, lines and transformers. These constraints include the voltage magnitude of the buses other than the PV buses, current through the cables, line and transformer and transmission line flow limits.

$$V_i^{\min} \leq V_i \leq V_i^{\max} \quad i \in N_{PV} \quad (8)$$

$$I_i \leq I_i^{\max} \quad i \in N_{Tr} \quad (9)$$

$$S_k \leq S_k^{\max} \quad k \in N_l \quad (10)$$

The bounds on the decision variables include the transformer tap change ratio, reactor and capacitor reactive power limits, and the wind turbine var settings.

$$tap_{Tr,i}^{\min} \leq tap_{Tr,i} \leq tap_{Tr,i}^{\max} \quad i \in N_{Tr} \quad (11)$$

$$Q_{WT,i}^{\min} \leq Q_{WT,i} \leq Q_{WT,i}^{\max} \quad i \in N_{WT} \quad (12)$$

$$Q_{C,i}^{\min} \leq Q_{C,i} \leq Q_{C,i}^{\max} \quad i \in N_C \quad (13)$$

$$Q_{L,i}^{\min} \leq Q_{L,i} \leq Q_{L,i}^{\max} \quad i \in N_L \quad (14)$$

The var limits for the wind turbines can be obtained from the the manufacturer supplied active/reactive power capability curve of the turbine. The tap position of transformer and capacitor banks represent discrete control variables. Mostly shunt reactors are also controlled stepwise but continuous versions are also available.

In this paper the reactive power dispatch problem for a given time period will be analyzed in two different formulations: optimization for the current operating point and optimization for a predicted time horizon.

(a) Optimization for the current operating point

In real-time reactive power management, an optimal power

flow as described above is performed at each time step for the given operating point. The reactive power generation capabilities of the wind turbines and the grid code requirements corresponding to the measured active wind power generation at that operating point are supplied to the OPF program [2]. The optimal decisions obtained from OPF are delivered as control signals to the various var sources. Similar optimization is performed for a new operating point at the next time step. This method is applied usually to transmission grids to adjust the reactive power generation in an optimal manner. However, in the transmission grid supplied by conventional power plants, the loading situation doesn't change very fast. Therefore, the OLTC tap activity is limited. However, in wind farms there are frequent changes in tap positions. When optimizing the current operating point the optimization objective is as presented in (1) but without considering the OLTC cost and only for a single time step. This kind of optimization can be repeated in certain time intervals, for example, every 5-15 minutes. The expected results will be optimal with respect to wind farm losses but at the expense of a large number of OLTC changes.

(b) Optimization for a predicted time horizon

In this approach OPF is performed for a given scenario which includes a set of future operating points for a certain time horizon T . All these operating points are optimized simultaneously with the objective function as defined in (1).

The wind power scenario for the considered time period results directly from wind speed forecast. In this paper the wind speed forecast method will not be discussed, but we assume that the forecast results are available. The concept of predictive control is shown in Fig. 2.

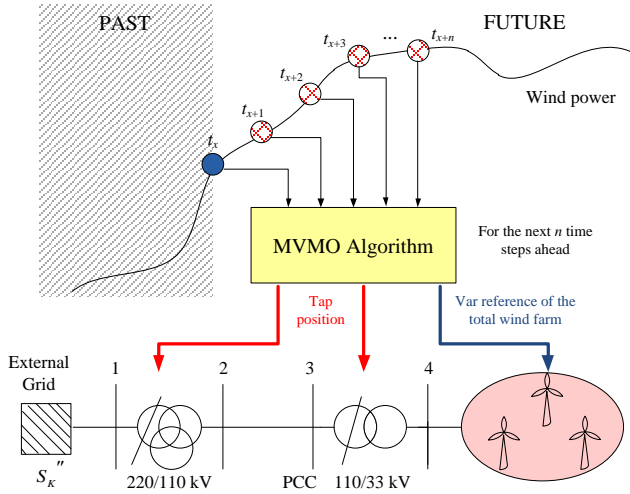


Fig. 2. Predictive control optimization by MVMO

Since the optimization is performed over the predicted time period, MVMO as the optimization algorithm receives the wind power prediction to n time steps ahead as an input. The OPF program suggests the optimal OLTC tap setting together with the optimal reactive power reference for the entire wind farm for the next n time steps.

III. MVMO ALGORITHM

The basic concept of MVMO exhibits certain similarities to other SOAs. A candidate solution of the optimization problem is characterized by a vector in the D -dimensional real space. The MVMO search process starts from an initial point \mathbf{x} randomly generated or specified by the user. The internal range of all variables in MVMO is restricted in $[0,1]$. That means the real boundaries have to be normalized to $[0,1]$. Three evolutionary operators are adopted in order to search for the optimum, namely selection, mutation and crossover. Apart from other evolutionary algorithms, the output of these operations is always inside $[0,1]$. Therefore, every trial vector never lies outside the search space. The new trial vector is de-normalized to the actual ranges only when the fitness function is evaluated. Then, the fitness of this trial vector is compared with those of the previous best solutions stored in the solution archive. Rules are set up to ensure that the archive never misses any quality solutions that have been discovered. The solution archive serves as the knowledge base for the algorithm. MVMO explores the search space until the pre-specified criteria are met. It should be noted that MVMO is a single-agent search algorithm because only a single offspring is generated in each iteration. Therefore, the number of fitness evaluations is identical to the number of iterations. Implementation steps of MVMO can be elucidated as the pseudo-code shown in Fig. 3.

1. Set MVMO parameters.
2. **Initialization:** Initialize an initial vector \mathbf{x} in $[0,1]$.
3. **Fitness evaluation:** De-normalize \mathbf{x} and evaluate the fitness.
4. **Termination:** Check the termination criteria. If yes, terminate MVMO. else, continue to step 5.
5. **Solution archive:** Store \mathbf{x} and its fitness f' to the archive if it is better than any of existing ones.
6. Based on the archived solutions, compute mean \bar{x}_i and variance v_i for each dimension i .
7. **Parent assignment:** Assign the best archived solution \mathbf{x}_{best} as the parent.
8. **Variable selection:** Select $m < D$ dimensions of \mathbf{x} .
9. **Mutation:** Apply the mapping function to the selected m dimensions.
10. **Crossover:** Set the remaining $D-m$ dimensions of \mathbf{x} to the values of \mathbf{x}_{best} .
11. Go to step 3.

Fig. 3. MVMO algorithm

In MVMO, only m selected dimensions of the offspring are updated by the mutation operator. The rest $D-m$ dimensions are assigned the values corresponding to \mathbf{x}_{best} . In every iteration, this process is equivalent to searching around \mathbf{x}_{best} only in the selected m axes. Four strategies for selecting the

variables were implemented in MVMO as shown in Fig. 4. From our experience, strategies 2 to 4 generally perform better than strategy 1. However, this observation is still neither general nor conclusive.

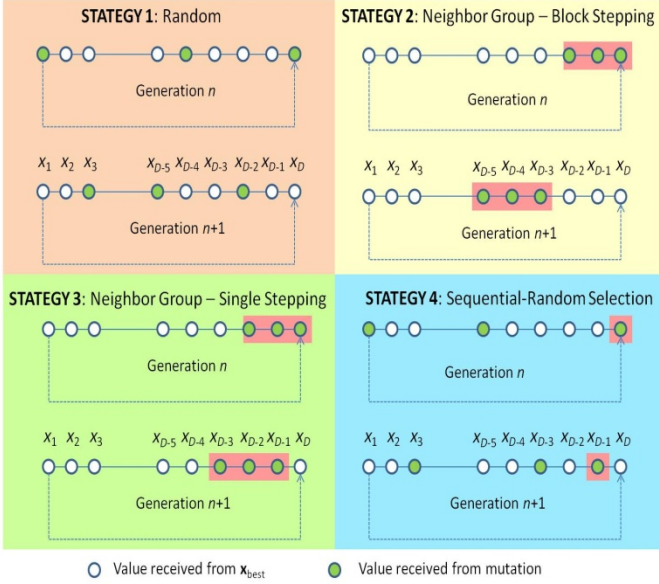


Fig. 4. Variable selection strategies ($m=3$)

As stated earlier, the major distinction of MVMO from other SOAs is the random sampling function for creating an offspring. Given a random number x'_i in $[0,1]$, the new value of the i component x_i will also be in $[0,1]$ and is determined by:

$$x_i = h_x + (1 - h_1 + h_0) \cdot x'_i - h_0 \quad (15)$$

where h_x , h_1 and h_0 are the outputs of the transformation mapping function based on different inputs given by:

$$h_x = h(u_i = x'_i), \quad h_0 = h(u_i = 0), \quad h_1 = h(u_i = 1).$$

The mapping function is parameterized as follows:

$$h(\bar{x}_i, s_{i1}, s_{i2}, u_i) = \bar{x}_i \cdot (1 - e^{-u_i \cdot s_{i1}}) + (1 - \bar{x}_i) \cdot e^{-(1-u_i) \cdot s_{i2}} \quad (16)$$

where s_{i1} and s_{i2} are shape factors allowing asymmetrical slopes of the mapping function. The slope is calculated by

$$s_i = -\ln(v_i) \cdot f_s \quad (17)$$

The asymmetrical slopes s_{i1} and s_{i2} are considered as modified slopes of ?? taking into account the position of the $x_{i,best}$ in relation to the mean \bar{x}_i . If $x_{i,best} < \bar{x}_i$, s_{i2} is increased, otherwise s_{i1} is increased by an asymmetry factor f_{asym} . Different slopes s_{i1} and s_{i2} allow the space to be searched below or even above the mean value. The scaling factor f_s enables the control of the search process during iteration. A small value of f_s (between 0.5 and 1.0) allows the slope of the mapping curve to increase and thus enable better exploration.

Values of f_s above 1.0 will result in a flat curve and thus lead to improved exploitation. It is recommended to start the search process with a smaller f_s and then increase it as the iteration progresses.

Fig. 5 demonstrates the mapping function for the uniform slopes equal to 10 and the search samples for two optimization variables within the original not normalized boundaries.

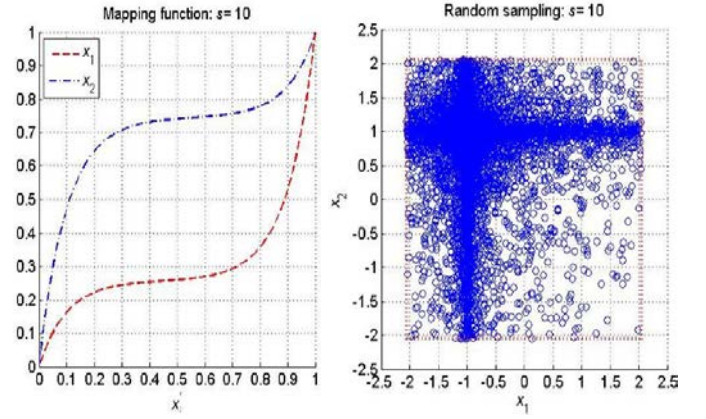


Fig. 5. Mapping function (left) and corresponding two dimensional searching space (right)

When the MVMO is adopted to solve nonlinear optimization problems, the constraints must be properly treated, one of which being to employ the penalty fitness function. As mentioned earlier, the control variables in MVMO are self-restricted due to the normalization in $[0,1]$. Based on the static penalty scheme, the integrated fitness function is defined by:

$$\min f' = f + \sum_{i=1}^n \lambda_i \max[0, g_i]^\beta \quad (18)$$

where f is the original objective function; n is the number of constraints; β is the order of the penalty term (usually 1 or 2); and g_i is the inequality constraint i represented by:

$$g_i(\mathbf{x}, \mathbf{u}) \leq 0 \quad (19)$$

where \mathbf{x} is the vector of state variables and \mathbf{u} is the vector control variables.

The MVMO algorithm used in this paper has no significant difference from the MVO presented in the previous work [10]. The algorithm name was changed for improved clarity because the mean and variance are not optimized. They are actually inputs of the mapping function.

IV. TEST WIND FARM

The layout of the test wind farm is shown in Fig. 6. It consists of 18 offshore wind turbines, each of 5 MW, and connected to the 220-kV-power grid through two 100 MVA transformers and one 110 kV underground cable of 70 km length. The PCC is considered at the 110-kV-side of the wind farm 110/33 kV transformer. The voltage at the wind turbine terminals is maintained between 0.92 and 0.97 kV where the nominal value is 0.95 kV. For all other nodes $\pm 5\%$ range around the nominal voltage is prescribed. Both transformers are equipped with OLTC.

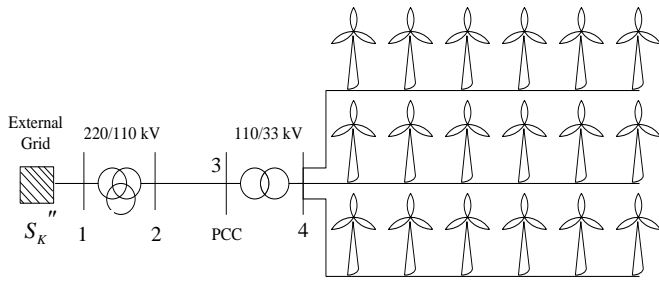


Fig. 6. Layout of the test wind farm

V. OPTIMIZATION OF THE CURRENT OPERATING POINT

Given the reactive power reference of the entire wind farm, an optimization task is carried out to allocate the reactive power output to each wind turbine in the farm. The transmission line to the external grid is not considered in this example, meaning that the only 110 kV node represented is the PCC. The optimization includes the 18 generator var outputs and the tap position of the 110/33 kV transformer as control variables. Fig. 7 shows the convergence of the active power losses over the iterations.

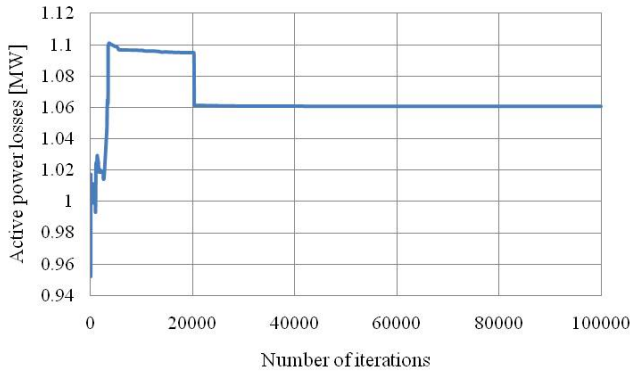


Fig. 7. Convergence of wind farm active losses

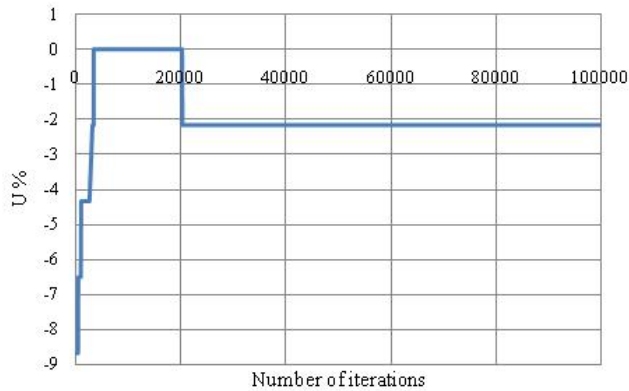


Fig. 8. Convergence behavior of OLTC

Initially the power loss increases due to the need to reach the reactive power interchange set point between PCC and wind farm. However after twenty thousand iterations the OLTC moved down one step (see Fig. 8) resulting in sudden reduction of losses. The behavior of the wind turbine control variables is shown in Fig. 9.

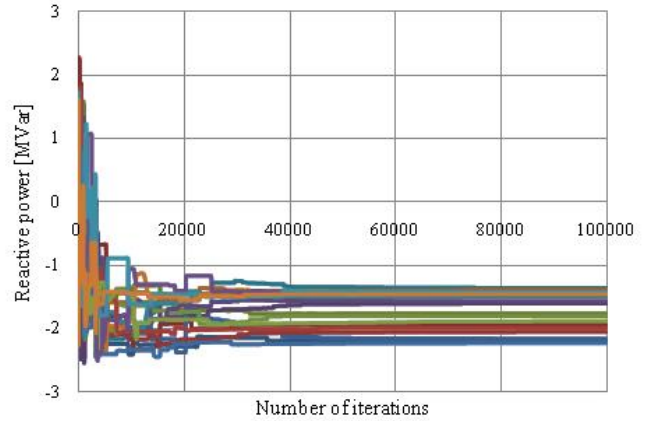


Fig. 9. Convergence behavior of wind turbine reactive power

As can be seen wind turbine reactive powers converge not before 40000 iterations. However, the wind farm power losses considered as the fitness of the optimization converge already after 20000 iterations. This shows that the change in the distribution of reactive power generation among the wind turbines does not affect the overall losses considerably. The conclusion becomes obvious when considers the small distances between the wind turbines which are about 500-600 meters. Despite the large number of iteration the optimization is performed within a few seconds by using ordinary PC.

The optimization shown in this chapter is carried out for the current operating point. The projection of wind power development in the next minutes and hours ahead is not considered. As a result, the optimization may suggest control actions which are, under circumstances, a few minutes later not reasonable due to the possible change of wind power in-feed. In the next chapter the authors show results of the predictive optimization approach as explained in chapter II that allows the minimization of the number of OLTC control actions by taking into account the projection of wind power.

VI. PREDICTIVE OPTIMIZATION

The proposed predictive control optimization is tested with the wind farm model as shown in

Fig. 2. However, the 33 kV wind farm collector grid is not included but the 110 kV transmission line including both transformers are considered. The optimization in this case provides the total wind farm reactive power reference and the OLTC positions for every 5 minute intervals over the optimization period T . The MVMO algorithm used for the simulation has the archive size of three solutions. The initial number of variables randomly changed in the selection process is set to six. The internal parameters of MVMO are set as follows: $f_s = 1$; $AF = 2.5$ and $s_d = 25$. The predicted wind profile with a sampling rate of five minute as shown in Fig. 10 is used for the simulation.

In this example, the MVMO algorithm suggests the optimal settings of reactive sources for the current and the next time steps ahead. Therefore, the planning horizon here is 30 minutes. The optimization is repeated 48 times until the end of the day.

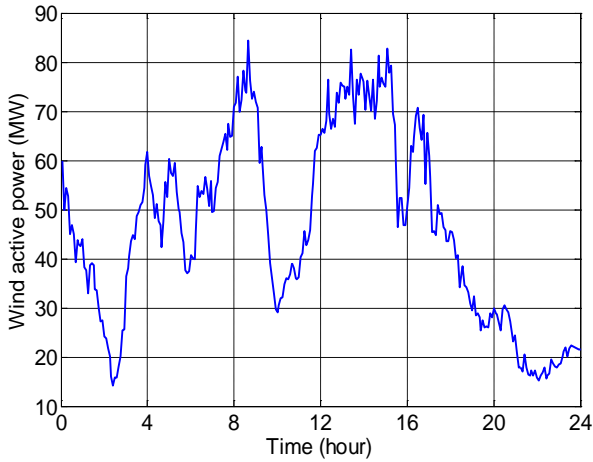


Fig. 10. Wind power variation

The dispatch curve of the 110/33 kV and 220/110 kV OLTC transformers is shown in Fig.11.

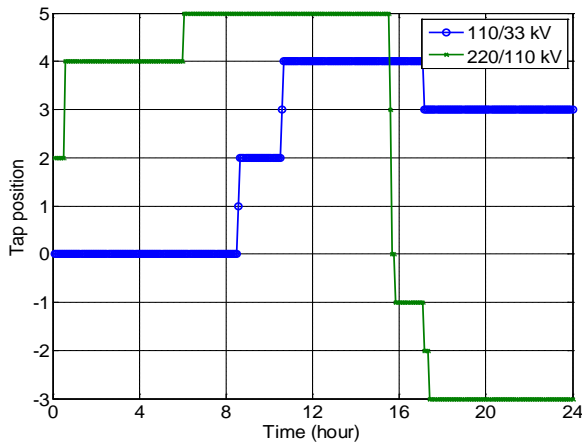


Fig. 11. OLTC tap positions in a daily operation

The total number of tap movements in the daily operation of the wind farm is 4 and 3, respectively. The energy costs are evaluated by 8 Eurocent per kWh and one OLTC movement by 10 Eurocent. Fig. 12 shows the required wind farm reactive power reference which is determined by the optimization in 5 minute intervals.

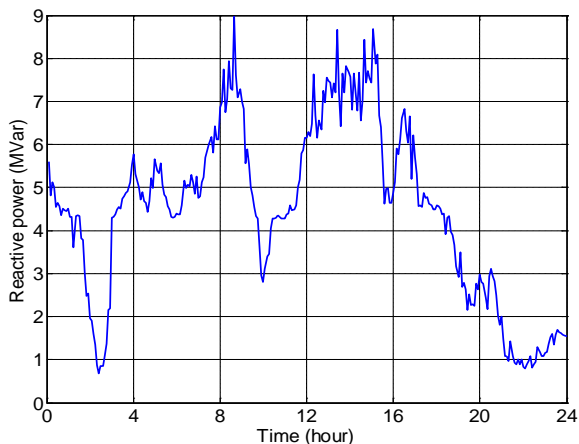


Fig. 12. Reactive power reference of the wind farm

Fig. 13 depicts the voltage profile at the two 110 kV nodes and the 33 kV wind farm bus bar. It can be noticed that the proposed predictive control strategy can help maintain the voltage level at grid buses within the permissible limit (here $\pm 2\%$ at the 33 kV bus and $\pm 5\%$ at the rest).

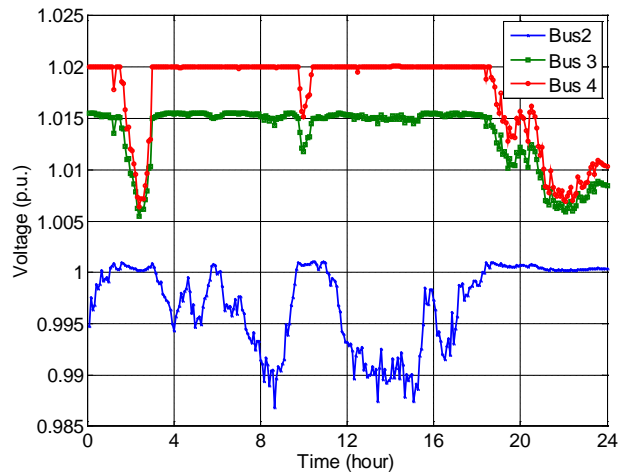


Fig. 13. Voltage profile in a daily operation

VII. ONLINE WIND FARM OPTIMIZATION

Large wind farms are usually equipped with wind farm controller. The objective here is to adjust the PCC reactive power, alternatively the power factor or the PCC voltage to the reference values by controlling each individual wind turbine. Fig. 14 shows the alternative PCC control options and the communication between wind farm and wind turbine controllers. The wind farm controller implemented in this study shows a PI behavior. The output is the reactive power that needs to be supplied by the whole wind farm and then distributed to each wind turbine. It should be mentioned that wind farm controller with the voltage as control output has also been in operation. In this case the deviation from the nominal terminal voltage required for optimal operation is sent to the wind turbines where a continuous voltage controller is implemented. Irrespective of the control schema implemented for the wind farm the optimization approach suggested here can be used with little modification to assign the optimal set point to each wind turbine. Without optimization usually the required reactive power is distributed equally to the wind turbines. However, it will not result automatically in minimum losses. Moreover, the voltage level on the wind turbine terminals may also differ considerably. To operate the wind farm with minimum losses and keep the voltage at the wind turbine terminals within acceptable thresholds different distribution factors has to be applied to the wind farm reactive power. The allocation factors are calculated based on the status and loading information received from the wind turbines periodically, e.g. every 15 minutes. The optimization task in this case is to determine the optimal allocation factors. It should be performed by taking into consideration the wind farm reference reactive power according to (5) or alternatively the voltage or power factor references in the PCC. Then the reactive power of each wind turbine is determined by

$$\Delta Q_i = \Delta Q_{\text{total}} \cdot d_i \quad (20)$$

where d_i is the distribution (allocation) factor assigned to wind turbine i and ΔQ_{total} is the wind farm controller output. The suggested approach allows adjusting the distribution factors to changing operating conditions but the wind farm control can also work without the optimization tool by simply using unity distribution factors. Additional var generation devices possibly connected to the PCC can be also included into the optimization easily.

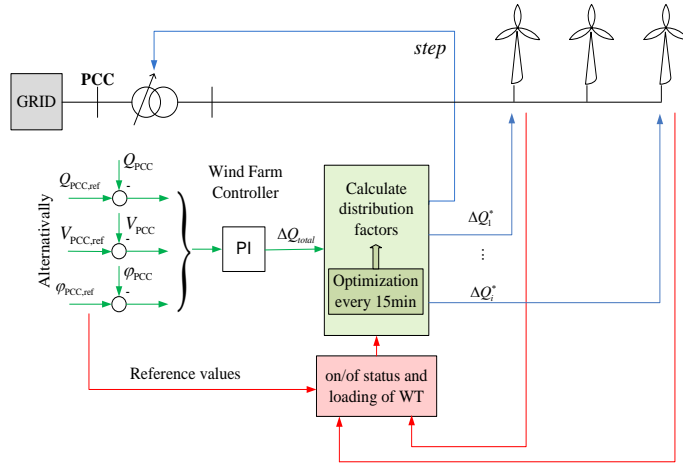


Fig. 14. Wind farm control schema including online optimization

VIII. CONCLUSION

In this paper different reactive power optimization approaches for wind farms are presented. The optimization for the momentary operating point allows minimizing the total losses within the wind farm but doesn't consider the OLTC costs, which are functions of the OLTC movements. Predictive optimization solves this problem by considering the number of tap changes in the objective function and by optimizing for a certain time horizon ahead. According to the approach suggested here the predictive optimization provides the var reference setting for the wind farm. The allocation of reactive power generation to each individual wind turbine is performed by the wind farm controller. The optimal distribution represents again an optimization task. How the optimization and the wind farm controller may work together online is also shown in this paper.

A new heuristic optimization algorithm called MVMO is used for all optimization tasks introduced in this study. The algorithm is simple and easy to implement. It shows excellent performance and robustness.

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IX. BIOGRAPHIES

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