Predictive Optimal Control of Wind Farm Reactive Sources

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***Abstract*—This paper presents two different optimization models for predictive optimal control of wind farm reactive sources. The models are formulated as a reactive power dispatch problem. The objective of this optimization task is to reduce the operation cost of the on load tap changing transformers by reducing the short term tap changes using a predictive optimal control. Wind generation is predicted by neural network. The stochastic nature of the wind generation is modeled as a binary tree for the stochastic tree method. The proposed methods are tested on an offshore wind farm and solved using particle swarm optimization algorithm.**

***Index Terms*— Artificial neural network, offshore wind farms, particle swarm optimization, reactive power dispatch, stochastic programming.**

I. INTRODUCTION

Offshore wind farms in Germany will contribute a significant portion of the total electricity generated in the country. Most of these wind farms will be connected to the high voltage grid at the point of common coupling (PCC) via AC submarine cables. According to the German grid code, wind farms should also provide reactive power to the grid. The requirement is defined alternatively as the power factor, the amount of reactive power supplied or the voltage at PCC. From the transmission utilities point of view, wind farm should operate like any other conventional generators. 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 devices like SVC or STATCOM are also considered. Optimal utilization of the available Var sources along with the transformer control constitutes the optimal reactive power dispatch problem. The reactive power dispatch [1] 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. However, the volatility of the wind poses a serious problem to the reactive power management of wind farms. In contrast to transmission grids the update of optimal settings of reactive sources is required more frequently. As a result the on load tap changing transformers have to be continuously regulated in order to maintain the voltage profiles in an acceptable and optimal range. This increases the operation and maintenance cost of the transformers.

In this paper the authors suggest a predictive control approach where actions are taken based on a 15-30 minutes forecast interval. The idea is to avoid short term transformer stepping by adapting the control to 15-30 minutes wind power expectation. To achieve this goal a Neural Network (NN) has been developed to forecast the wind scenario for the considered time frame. However, the forecast involves huge error characterized by an uncertain prediction interval. Therefore, the predictive control is considered as a stochastic optimization problem [2] taking into account different scenarios. To minimize the number of transformer stepping it is necessary to consider the corresponding costs in the optimization objective. While the number of transformer stepping is limited, control actions not resulting in cost increase are allowed to adjust the reactive power generation more frequently.

The effectiveness of different problem formulations is tested on an offshore wind farm. All the optimizations in this paper are performed using particle swarm optimization (PSO) algorithm [3].

II. WIND FARM MODEL

The wind farm network [4] considered for this research is as shown in fig. 1. The wind farm consists of 80 turbines each rated at 5MW. All the wind turbines are represented as a single equivalent for computational simplicity. The wind farm is connected to the grid at the PCC through two parallel 70km submarine cables. The turbines are nearly 70-80 km away from PCC. The internal power transmission is realized by 33/0.8 kV transformer, 14 parallel 2.5km 33kV cables, two parallel 70km submarine cables and two step up on load tap changing transformers rated at 150/33 and 380/150 kV respectively. The excessive charging current of the submarine

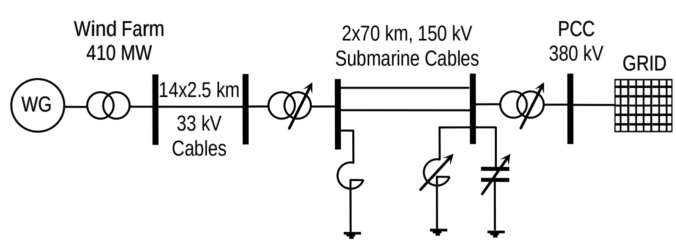

Fig. 1.Test offshore wind farm connected to the grid

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ables is compensated by connecting shunt reactors on either side of each cable. The reactor on the onshore side of the cable can be continuously adjustable. The onshore side is also connected with an adjustable capacitor.

III. 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 loss, improve the voltage profile in the system and also minimize an uneconomical large number of tap changes of the transformers while satisfying the unit and system constraints. The objective function is formulated as a multi-objective function as shown below:

$$\text{minimize } w_1 \mathrm{Tr}_{\mathrm{cost}} + w_2 \mathrm{P_L} \tag{1}$$

where w_1 and w_2 are the weight coefficients. $\mathrm{Tr}_{\mathrm{cost}}$ is the total operation cost of the transformers which is a function of the number of tap changes.

$$\mathrm{Tr}_{\mathrm{cost}} = \sum_{i=1}^{N_{Tr}} w_3 \sum_{t=1}^{T} \left| \mathrm{tap}_{\mathrm{Tr,i}}^{\mathrm{t}} - \mathrm{tap}_{\mathrm{Tr,i}}^{\mathrm{t\text{-}1}} \right| \tag{2}$$

The weight factor w_3 corresponds to the cost for one tap change. $\mathrm{P_L}$ is the total power loss calculated as shown below:

$$\mathrm{P_L} = \sum_{k=1}^{N_l} \mathrm{P}_k \tag{3}$$

Where $\mathrm{P_k}$ is the real power losses in line k and $\mathrm{N_l}$ is the total number of lines including cables within the wind farm:

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

The system constraints include the TSO specified grid code [5] requirements as shown in Fig. 2. The wind farm must be able to operate at any of point within the area marked in the diagram. Utilities can define the operating points required as power factor, reactive power or voltage reference at PCC. In this paper the power factor definition is used. The power factor requirement at the PCC is in accordance with (5).

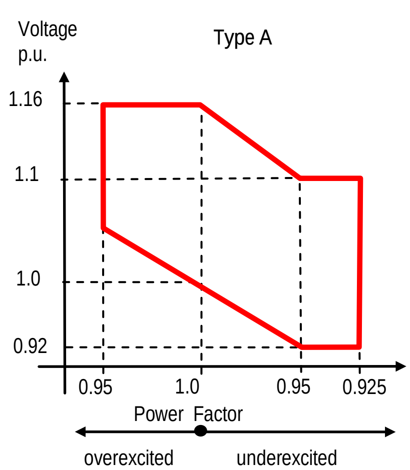

Fig. 2. Example for grid code requirement at PCC

$$\cos\phi_{\mathrm{PCC}} = \cos\phi_{\mathrm{ref}} \tag{5}$$

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.

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

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

Where $\mathrm{P_i/Q_i}$ is the net active/reactive power injected at bus i, $\mathrm{Y_{ij}}$ is the admittance matrix corresponding to the $\mathrm{i^{th}}$ row $\mathrm{j^{th}}$ column and θ_{ij} is the difference in the voltage angle between the $\mathrm{i^{th}}$ and $\mathrm{j^{th}}$ 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 (V) and current through the cables, lines and transformers (I). These constraints include the voltage magnitude of the buses other than the PV buses, current through the cables, lines and transformers and transmission line flow limit.

$$V_i^{\mathbf{min}} \le V_i \le V_i^{\mathbf{max}} \quad i \in N_{\mathrm{PV}} \tag{8}$$

$$I_i \le I_i^{\mathbf{max}} \quad i \in N_{\mathrm{Tr}} \tag{9}$$

$$S_k \le S_k^{\max} \quad k \in N_l \tag{10}$$

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

$$tap_{\mathrm{Tr},i}^{\min} \le tap_{\mathrm{Tr},i} \le tap_{\mathrm{Tr},i}^{\max} \quad i \in N_{\mathrm{Tr}} \tag{11}$$

$$Q_{\mathrm{WT},i}^{\min} \le Q_{\mathrm{WT},i} \le Q_{\mathrm{WT},i}^{\max} \quad i \in N_{\mathrm{WT}} \tag{12}$$

$$Q_{\mathrm{C},i}^{\min} \le Q_{\mathrm{C},i} \le Q_{\mathrm{C},i}^{\max} \quad i \in N_{\mathrm{C}} \tag{13}$$

$$Q_{\mathrm{L},i}^{\min} \le Q_{\mathrm{L},i} \le Q_{\mathrm{L},i}^{\max} \quad i \in N_{\mathrm{L}} \tag{14}$$

The Var limits for the wind turbines can be obtained from the active/reactive power capability curve for the turbine supplied by the manufacturer. 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 three different formulations: node, deterministic and stochastic methods.

(a) Node Method

In real-time reactive power management, an optimal power flow as described above is performed at each time step (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 [6].

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. In the transmission grid supplied by conventional power plants, the loading situation doesn't change very fast. Therefore, the transformer tapping is limited. However, in wind farms there are frequent changes in tap positions. The optimization objective in this method is as presented in Eq. (1).

(b) Deterministic Scenario Method

In this approach OPF is performed for a given scenario which includes a set of future operating points. All these operating points are optimized simultaneously. The objective is as follows:

$$\text{minimize} \sum_{t=1}^{T} w_1 \mathrm{Tr}_{\mathrm{cost},t} + w_2 \mathrm{P}_{\mathrm{L},t} \qquad (15)$$

The optimization is performed for a certain future time horizon T. The wind power scenario for the considered time period is the result of wind power forecast. In the next section, a neural network method forecasting wind power development in the next 15-30 minutes ahead is discussed. Since the optimization is performed over the predicted time period, the OPF program generates solutions which result in minimum tap changes along with minimum energy loss for this time period. However the credibility of this approach depends on the accuracy of the wind scenario prediction.

(c) Stochastic Scenario Method

This method presents the planning of the reactive power management not only for a single scenario but for several scenarios taking into account the stochastic nature of wind and uncertainties in wind power forecast. A two stage stochastic programming formulation is used in this study. The stochastic nature of the wind generation is modeled as a binary tree (Fig. 3). The tree consists of several decision making points called the nodes. Each node corresponds to a distinct operating point. The evolution of the uncertainty starts with node n_1 (root node) at t=0. The node then branches of into node n_2 and n_3 with transition probability $\pi_{n2/n1}$ and $\pi_{n3/n1}$ respectively. The corresponding node probability is calculated by multiplying the transition probability with their parent node probability. The branching implies that at time t=1, the wind generation can evolve as either n_2 or n_3. These nodes further evolve until the planning horizon. The path from the parent node to a node in the final time stage constitutes a scenario. Stochastic programming is then used to incorporate these scenarios or nodes in the objective function.

In this modeling approach, the decisions are made in two stages as shown in Fig. 4. The first stage decisions, transformer tap settings are made without anticipating the outcome of the wind uncertainty. After the uncertainty is revealed, some recourse actions need to be taken, to pacify the reactions caused by the first stage decisions. These recourse actions are in the form of the second stage decisions: Q_{WT}, Q_C

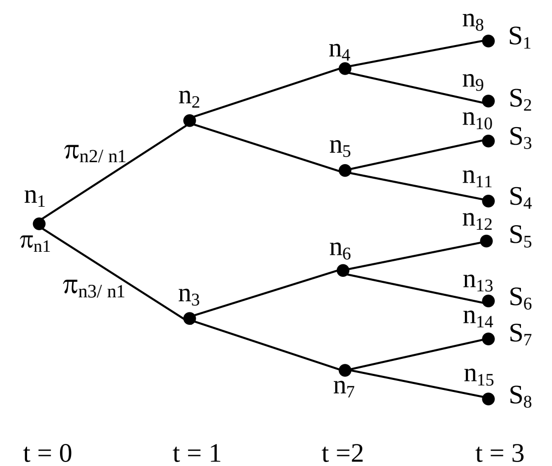

Fig. 3. Binary tree modeling of wind uncertainty for T=15mins

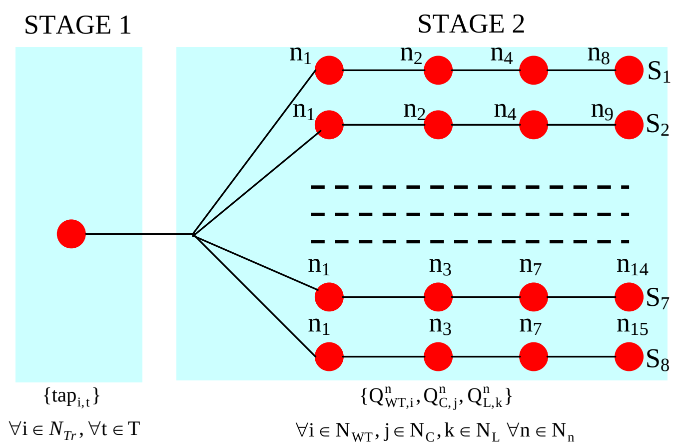

Fig. 4. Two stage stochastic programming decision model

and Q_L. The objective of this method is to minimize the direct costs, transformer operation cost incurred by the first stage decisions and the expectation of the recourse costs, total power

$$\text{minimize} \begin{cases} w_1 \sum_{t=1}^{T} \mathrm{Tr}_{\mathrm{cost},t}(tap) + \\ w_2 \sum_{n=1}^{N_n} \pi_n \mathrm{P}_{\mathrm{L},n}(tap, Q_{WT}, Q_C, Q_L) \end{cases} \qquad (16)$$

loss which is a function of the first and second stage decisions. The model therefore generates first stage decisions which results in minimum recourse actions i.e. the transformer tap settings made in the first stage will be optimal to all the scenarios considered in the second stage. However, the reactive power generation is adapted according to the grid requirements and the current wind power scenario.

IV. Wind Power Prediction

Short term prediction of wind speed/power can be classified into two main groups based on the underlying model. In the first category, meteorological data of wind, such as wind velocities and directions, are used to construct numerical weather prediction models. The second group of approaches employs data mining techniques to map the relation between the selected inputs and the target. In this paper, we have developed an artificial neural network (ANN) to predict the wind power generation of the future *n* time steps (t_{x+1} to t_{x+n}) as shown in Fig.5. The ANN uses the inputs consisting of wind power generation of the current (t_x) and past *m* time steps (t_{x-1} to t_{x-m}). Some information such as wind velocity or wind direction can be additionally supplied as inputs to improve the prediction accuracy. The ANN model used in this study is configured with four inputs consisting of wind power from the current and eight from the delayed time steps (*m*=8). The training session is carefully conducted in order to map the relation between the designated input features and the wind power of the future three time steps (*n*=3).

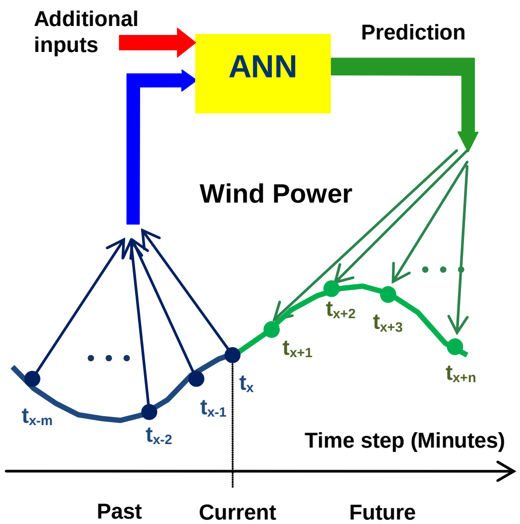

Fig.5 Wind power prediction by ANN

The training data encompass a time series of five-minute average wind power generation in MW at 8000 time steps collected from the operation in April 2003 of the wind farm discussed in section II. A feed-forward network with two hidden layers was developed using Matlab neural network toolbox [8].

In the next stage, a testing time series of 288 time steps, which have never been presented during the training session, are given to the trained ANN to validate the accuracy of prediction. Fig.6(a) shows the comparison between the ANN prediction and the corresponding measured wind power profile on a day and the corresponding absolute prediction errors in terms of percentage relative to nominal wind farm power (400 MW) are plotted in Fig. 6(b). The average error is 1.96% and the maximum error is 8.39%. These results are quite acceptable. It can be further observed that the developed ANN can discover the direction of wind power changes over the day very well. However, it may find difficulties in predicting some drastic wind changes as reflected by relatively higher prediction errors in Fig.6 (b). From a practical point of view, the ANN can be regularly trained by a contemporary set of data to achieve the more accurate prediction.

It should be emphasized here that the primary objective of this paper does not focus on the wind power prediction but on the predictive control measures that account for any probable wind power change in the next operation horizon (15 minutes as applied here). The optimization approach is so flexible that it can incorporate a better wind forecast tool.

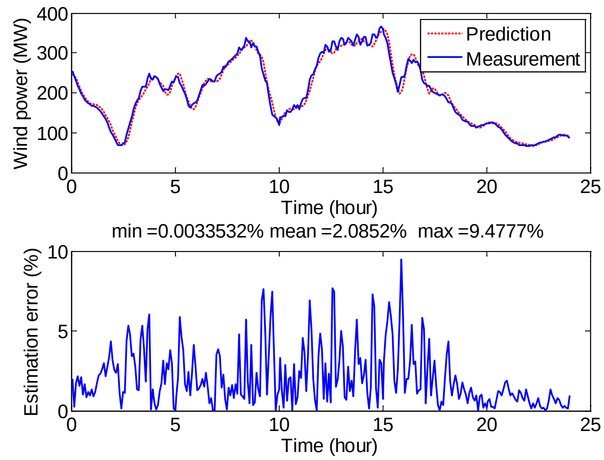

Fig.6 Validation of wind power prediction (a) comparison between prediction and measurement (b) absolute prediction error

V. Optimization Algorithm

Particle swarm optimization (PSO) technique is used for demonstrating the effectiveness of various modeling methods for reactive power management. PSO is a population based global search algorithm inspired from the social behavior of birds. A particle represents a solution to the given problem and the group of particle is called the swarm. Each particle is associated with a fitness value which is calculated using the objective function in (1). The particles can be evaluated based on this fitness value. The particles explore the search space with a certain velocity. This velocity is derived from the experiences of the particle's own performance and the experiences gained from the performance of the particle's best performing neighbor. Each particle associates with a group of neighbors selected from the swarm [9]. The particles trace the optimal solution by cooperation and competition among their neighbors.

The constraints are handled using adaptive penalty function approach [10]. The penalties and thereby the fitness of the particles adapt to the requirement and necessity of the swarm. For example if the swarm has no feasible particles, the penalized objective function is modeled to minimize the constraint violation and on the other hand when the swarm is in search of optimal regions, then the new objective automatically transforms to minimize the objective as well the constraint violation. The prominent feature of this approach is that it identifies the right set of infeasible particles which can help the search process. Not all information carried by the infeasible particles is important. Different set of infeasible particles are important at different stages of the search process. The proposed penalty function technique designs the penalty terms based on the search procedure and therefore no problem dependent information is required to formulate the penalties. The penalties are automatically adapted to the requirements of the swarm. There are as such no penalty coefficients tuning or redefinition of the penalty function for a new application. The penalty function once defined can be used without any restructuring on any optimization problem.

The decision variables for conducting the reactive power dispatch on the offshore wind farm shown in Fig. 1 consists of the reactive power generation of the wind turbine (continuous variable), transformer tap changer position (discrete variable) for 150/33 and 380/150 kV transformer, variable reactor (continuous variable) and variable capacitor (discrete variable). There are 13 discrete steps between ±12% for both the OLTC transformers and the capacitor has 21 discrete steps. The particle which represents the set of decision variables is a vector of these five variables for node method. Whereas for scenario method, the particle consists of several sets of these five decision variables. Each set corresponds to an operating point at a given time step. The set of decision variables is as follows:

$$\left\{ tap_{1,t}, tap_{2,t}, Q_{WT,t}, Q_{C,t}, Q_{L,t} \right\} \forall t \in T \tag{17}$$

So for a planning period of 15 minutes with a sampling time of 5 minutes i.e. t=0, 5, 10 and 15 there are four operating points and therefore there are four sets of these five decision variables or 20 variables. In the tree method, for the same planning period, the particle is as shown below:

$$\left\{ tap_{1,t}, tap_{2,t}, Q_{WT,n}, Q_{C,n}, Q_{L,n} \right\} \forall t \in T, \forall n \in N_n \tag{18}$$

Assuming that the wind generation is modeled as a binary tree as shown in Fig. 3, there will be 15 operating points (N_n=15). The number of decision variables will be 2×4 for the two transformers and 15×3 for the remaining three Var sources or 53 variables.

VI. Test Results

The three proposed reactive power dispatch modeling techniques are tested on the offshore wind park model shown in Fig. 1. The PSO algorithm used for the simulations has a swarm size of fifteen particles with a neighborhood size of five particles. The forecasted wind scenario by the NN and the prediction error for the planning period of T=15 min is given in Table I. The measured scenario represents the actual measurements taken. The wind scenario corresponds to the wind profile shown in Fig.6 from 14:50 to 15:05. For the tree method the wind generation is modeled as a binary tree where each node has two successive nodes describing the extreme limits of the forecast data i.e. $P_{WT} = P_{WT} \pm error * P_{WT}$. This results in a scenario tree as shown in Fig. 3 with eight scenarios and fifteen nodes. In reality, the node method is applied on the actual measured scenario and the deterministic scenario method on the forecasted scenario. But for detailed problem analysis, additional simulations were performed for all the scenarios of the binary tree in Fig. 3. The initial tap setting for the 150/33 and 380/150 kV transformers is 7 and 10 respectively. These initial settings are the optimal settings obtained by the optimization carried out at the previous time period. The cost of the transformer operation (w_3) is assumed to be 1€/tap change.

TABLE I
WIND DATA

Time/minutes	t=0	t=5	t=10	t=15
Forecast wind scenario(MW)	351.472	350.579	312.699	351.338
Measured wind scenario(MW)	351.472	353.054	310.829	356.608
prediction error	0.0%	1.0%	1.1%	1.2%

(a) Node Method

This method presents the operation mode for the reactive power management. Optimization is performed at the current operating point. In this case study there was no prediction for the operation. The total energy loss (W_L) and transformer changes for a period of 20 minutes is calculated by performing the optimization at each operating point on the measured scenario individually.

TABLE II
TOTAL ENERGY LOSS IN 20 MINUTES INTERVAL FOR THE MEASURED SCENARIO USING NODE METHOD

time/minutes	t=0	t=5	t=10	t=15	Σt=20
W_L(MWh)	0.675	0.7	0.55	0.69	ΣW_L=2.615
Transformer Tap Changes(tap)	2	1	1	2	Σtap_{Tr} =6

TABLE III
TOTAL ENERGY LOSS IN 20 MINUTES INTERVAL FOR THE SCENARIOS IN THE BINARY TREE USING NODE METHOD

scenario	W_L(MWh)				ΣW_L
	t=0	t=5	t=10	t=15	
S_1	node 1	node 2	node 4	node 8	2.675
	0.675	0.73	0.55	0.72	
S_2	node 1	node 2	node 4	node 9	2.615
	0.675	0.73	0.55	0.66	
S_3	node 1	node 2	node 5	node 10	2.665
	0.675	0.73	0.54	0.72	
S_4	node 1	node 2	node 5	Node 11	2.605
	0.675	0.73	0.54	0.66	
S_5	node 1	node 3	node 6	Node 12	2.62
	0.675	0.675	0.55	0.72	
S_6	node 1	node 3	Node 6	Node 13	2.56
	0.675	0.675	0.55	0.66	
S_7	Node 1	node 3	node 7	Node 14	2.61
	0.675	0.675	0.54	0.72	
S_8	node 1	node 3	node 7	node 15	2.55
	0.675	0.675	0.54	0.66	

The results of these simulations are listed in Table II. The total energy loss for the 20 minutes operation time period amounts to 2.615 MWh and nearly six tap changes were required. Additional node simulations were performed for each scenario in the considered binary tree to illustrate how the transformer tap changes vary with the changes in wind scenario. For example, scenario S1 in Fig. 3 consists of four nodes: n1, n2, n4 and n8. OPF is performed at each node separately and the results are presented in Table III and Table IV. The last column in Table III indicates the cumulative energy loss for a period of 20 minutes. The average energy loss for 20 minutes using this method is nearly 2.608 MWh. Table IV indicates the tap changes observed at each time step for each scenario. A minimum of four tap changes are required to balance the grid requirement and other local reactive demand in the wind farm network. The tap changes are observed at almost all time stages. This is obvious as the optimal settings at one operating point may not be best initial setting for the following operating point. This results in excessive operation of the transformers.

TABLE IV
TRANSFORMER TAP CHANGES IN 20 MINUTES INTERVAL FOR THE SCENARIOS IN THE BINARY TREE USING NODE METHOD

scenario	Transformer Tap Changes				Σtap_{Tr}
	t=0	t=5	t=10	t=15	
S_1	2	0	2	1	5
S_2	2	0	2	2	6
S_3	2	0	1	1	4
S_4	2	0	1	2	5
S_5	2	1	2	1	6
S_6	2	1	2	2	7
S_7	2	1	1	1	5
S_8	2	1	1	2	6

(b) Deterministic Scenario Method

In this case study a single wind scenario predicted by the NN is used (Table I). This method presents the planning of the operation for 15 minutes time period. The optimization is carried out for the entire forecast scenario simultaneously and the results are presented in Table V. The total energy loss amounts to 2.816 MWh and only three tap changes were required. Additional simulations were conducted on different scenarios in the binary tree to verify how the transformer tap changes vary with the changes in wind scenario. Table VI presents the results assuming that each of the scenarios is a prediction from the NN. The average losses are approximately 2.692 MWh. The maximum tap changes required in this analysis is only three.

Most of the scenario do not show any tap changes during the planning period. Most of the tap changes observed are at time t=0. This indicates a very drastic change in the operating point prior to time t=0. The tap changes are reduced because the optimization tries to adjust the tap settings at one operating point such that it is also an optimal initial setting for the following operating point and so on.

TABLE V
ENERGY LOSS AND TRANSFORMER TAP CHANGES IN 20 MINUTES FOR THE FORECAST SCENARIO USING DETERMINISTIC SCENARIO METHOD

Transformer	Transformer Tap Changes				Σtap_{Tr}
	t=0	t=5	t=10	t=15	
150/33	0	0	0	0	0
380/150	3	0	0	0	3
Total W_L			2.82 MWh		

TABLE VI
ENERGY LOSS AND TRANSFORMER TAP CHANGES FOR 20 MINUTES USING DETERMINISTIC SCENARIO METHOD

scenario	Transformer Tap Changes				Σtap_{Tr}	ΣW_L
	t=0	t=5	t=10	t=15		
S_1	2	0	0	0	2	2.795
S_2	2	0	1	0	3	2.691
S_3	3	0	0	0	3	2.837
S_4	2	0	1	0	3	2.666
S_5	2	0	0	0	2	2.579
S_6	2	0	0	0	2	2.647
S_7	2	0	0	0	2	2.746
S_8	2	0	0	0	2	2.607

(c) Stochastic Scenario Method

The binary tree shown in Fig. 3 is used for modeling the stochastic nature of the wind generation. The results obtained by the two stage stochastic programming approach used for solving the reactive dispatch problem are shown in Table VII. The tap settings for the two transformers at various time stages are shown in Table VII. The 150/33 kV transformer required two tap changes at the initial time step. The number of tap changes observed is only two. The total energy loss is less compared to the remaining two methods.

TABLE VII
ENERGY LOSS AND TRANSFORMER TAP CHANGES FOR 20 MINUTES USING STOCHASTIC TREE METHOD

Transformer	Transformer Tap Changes				Σtap_{Tr}
	t=0	t=5	t=10	t=15	
150/33	2	0	0	0	2
380/150	0	0	0	0	0
Average W_L			2.563MWh		

The results from Table II, V and VII indicate that direct control (node method) of the Var sources in the wind farm will result in additional tap changes compared to the predictive control (scenario or tree method). The quality of the solutions generated by these models depends on the accuracy of the wind power measurement or forecast. But it is conclusive from the tests conducted on various scenarios (results presented in Table IV and VI) that the overall performance of the scenario method is far better than the node method. The stochastic tree method generates very high quality solutions. However this method drastically increases the problem complexity and requires far greater computational time compared to the other methods. The CPU time used in each method for 20 minute planning horizon with 100 generations of PSO is summarized in Table VIII. For the binary tree, each fitness evaluation in the optimization process requires 15 power flow calculations. The ratio of CPU times used in methods 3 to 1 shown in Table VIII is 15.27. These calculations if performed sequentially will involve huge delay time. Therefore parallel computing should be used to considerably reduce the computation time.

TABLE VIII
CPU TIME USED FOR 100 PSO GENERATIONS BASED ON DIFFERENT METHODS IN THE 20 MINUTE PLANNING

Method	No.of variables	CPU time (s)
1. Node	5	25.7580
2. Deterministic	20	99.4680
3. Stochastic	53	393.4200

To demonstrate the effectiveness of the proposed method, optimization based on deterministic scenario method is used to determine the optimal settings of Var sources. In this study, the planning time period is 20 minutes. The optimization is repeated for 72 times until reaching the end of the day. The initial tap settings of the two transformers are set to 7 and 10 similarly to the earlier simulations. The temporal change of tap position of the two transformers is shown in Fig.7. It can be observed that tap positions do not change so frequently in response to the fluctuating wind profile. The drastic changes of tap positions are required due to the sudden changes of wind power. The number of tap position changes is 54 and 31 for 33/150 and 150/380 kV, respectively. The proposed predictive control method can help avoid excessive transformer operations which lead to shorter life time expectancy and greater maintenance.

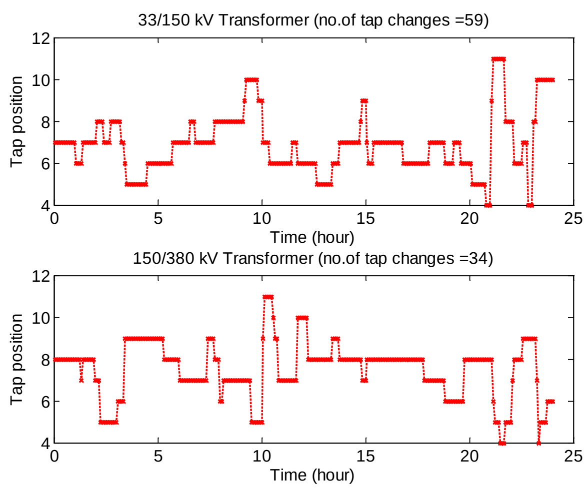

Fig.7 Transformer tap position in a daily operation

VII. CONCLUSION

A deterministic scenario method and a stochastic tree method have been successfully applied for predictive control of wind farm reactive sources. The analysis presented in the paper indicate that the predictive control results in optimal operation of the wind farm with reduced transformer tap changes and minimum energy loss than the direct control of Var sources. Although the deterministic scenario method provides optimal solutions with reduced transformer tap changes, the credibility of this approach depends on the accuracy of the forecast. The stochastic tree method considers the uncertain nature of the wind generation and therefore provides robust solutions.

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