Reactive Power Management in Offshore Wind Farms by Adaptive PSO

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Abstract: **According to the new grid codes, wind parks must operate similar to other conventional power plants. Offshore wind parks are connected to the main grid with long cables and reactive power management is a big concern to the operators in the changing wind power conditions. This paper addresses the optimal reactive power dispatch (ORPD), which is a mixed-integer nonlinear optimization problem. The integer variables in ORPD are tap positions of the transformers, switching of cables and switched reactors, if present. A new adaptive particle swarm optimization (APSO), which is free from tuning of population size and is based on different sized groups of particles called "Tribes", is used to solve the ORPD problem. The proposed APSO is embedded in the Newton-Raphson load flow program. The effectiveness of the proposed algorithm is demonstrated on a real offshore wind farm, which is currently in planning stage, in Germany.**

Index Term: **Wind Energy, Reactive Power Scheduling, Particle swarm optimization, Wind power interconnection**

I. Introduction

WIND energy technology for electric power generation has been improved dramatically in the last 20 years in terms of efficiency, availability, reliability and cost. Wind farms, both offshore and onshore, today expect an availability of 98% or more. Wind power is the fastest growing energy generation technology in the world. In Germany, which is the largest producer of wind electric energy in the world, the installed wind energy generating capacity was 20,622MW with 18,685 wind turbines at the end of 2006 [1] and is expected to increase in future by retrofitting onshore wind parks [2]. This will be achieved by changing the old turbines by new ones with taller towers and, thus, higher rated output power. Most of the planned offshore wind farms will be connected to the 400-kV grid via 150-kV AC submarine cables.

Wind farms are becoming an increasingly common off-shore and on-shore sights but due to the geographical conditions of wind farms, transporting the power from the wind energy sources to the grid in an efficient and economical manner is one of the major concerns of policy makers and system operators [3]. Normally, medium and large capacity wind farms are connected to the grid at medium and high voltage levels. Long radial lines and cables are required to evacuate power from the remote wind farms. Detailed system planning studies are required for building new transmission lines/cables to provide better stability and reliability, and to avoid the system congestions. Over the past several years, many investigations of wind's impacts on power system operation and operating cost have been carried out [4]. Mainly, the impacts depend on the wind park location, generation capacity, grid interconnection point, network configurations etc.

Due to the large penetration and continuous improvement in the wind power technology, wind farms must fulfil almost the same requirements as the conventional power plants. According to the German grid code, wind farms have to supply not only active power but also reactive power into the grid [5]. The requirements are defined with respect to the power factor as a function of the voltage at the point of common coupling (PCC) with the main grid. Offshore wind parks are connected to the grid via long AC submarine cables. For secure system operation and to provide variable reactive power generation other reactive power sources like shunt reactors, capacitor banks or even FACTS may also be connected. On-load tap changing (OLTC) transformers impact the reactive power generation indirectly by varying the voltage level. The available reactive power sources must be utilized properly during both steady-state and dynamic conditions for efficient and secure operation of the system. Thus, the reactive power management becomes an integral issue in the grid-connected offshore wind parks and can be formulated as a non-linear mixed integer optimization problem.

Particle swarm optimization (PSO) method as introduced by Kennedy and Eberhart [6,7] is a self-educating stochastic optimization algorithm that can be applied to any linear, nonlinear, mixed-integer optimization problem having continuous and/or discontinuous objective and constraint functions. PSO has many prominent merits over the other evolutionary algorithms. It has a high probability of finding a global minimum. Different versions of PSO have been suggested and have been successfully applied to the power system problems [8-12]. References [8-11] have used PSO for optimal reactive power dispatch considering different objectives. However, none of the ORPD papers utilizes adaptive PSO, which gives a faster and more robust optimal search and does not require parameter tuning.

In this paper, an adaptive particle swarm optimization (APSO) technique has been introduced for optimal reactive

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power management in an offshore wind park, may be for the first time. The wind power system (up to the main grid) loss has been minimized subject to the reactive power constraints according to the grid code requirements. The effectiveness of the proposed technique has been demonstrated on a real offshore wind park energy system and results are discussed. The algorithm is very fast and can be used for on-line application in VAr management. This paper could be a guideline for policy makers and system operators to promote wind power in terms of the system reliability and security.

II. Reactive Power Sources and Grid Requirements

A. Offshore Wind Farm: A System Description

Offshore wind parks are normally connected to the main grid using long cables (at least two cable to increase the reliability of the transmission system) having step-up transformers at both ends as shown in Fig. 1. Due to excessive charging currents of cables, line reactors are permanently connected at both ends of the cables. Apart from these, switched reactors may also be connected in the system to take care of voltage increase during low power generation periods and synchronization. To provide fast and continuous VAr control FACTS devices, such as thyristor controlled reactors (TCR), static VAr compensator (SVC), static synchronous compensator (STATCOM) etc. are also proposed. But due to excessive cost, the application of these devices is limited.

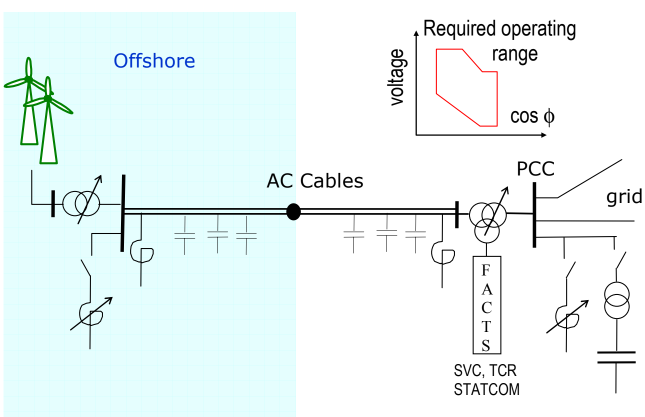

Fig. 1.Grid connected offshore wind park.

B. Reactive Power Capability of Wind Energy System

Variable speed wind turbines are equipped with voltage source converters. Focusing on the converter, two types of turbines have to be distinguished: fully converted machines and doubly-fed induction machines (DFIM). For the first one, the converter must be designed for the full rated power of the machine. For the latter one, the converter has to provide only one third of the rated power. In this paper, the doubly-fed induction machine has been considered but the method suggested is applicable also to the full size converter systems. The stator of the DFIM is directly connected to the grid while the rotor winding is connected using a voltage source converter (VSC). By supplying a voltage with variable frequency and variable amplitude to the rotor circuit, the shaft speed can be optimally adapted to the wind speed. The rotor-side converter (RSC) usually controls active and reactive power of the machine while the line-side converter (LSC) keeps the voltage of the DC-circuit constant. However, the LSC is also able to generate some reactive current until the maximum converter current is reached.

Fig. 2 shows a typical reactive power capability curve (P-Q characteristic) of doubly-fed induction generators used in wind farms. The reactive power capability (in the first quadrant) of a doubly fed induction generator depends on the LSC and RSC converters capability, as the maximum reactive and active powers of the converter are limited by the maximum absolute current, and the magnetizing current of the induction generator's characteristic. Thus, such P-Q characteristics have two special features: machines can absorb more reactive power in under excited mode than generate reactive power in overexcited operation. Additionally, turbines are able to feed reactive power even if no active power is fed. Following the given characteristic in Fig. 2, it is very desirable to reduce active power and increase reactive power during fault situations. Also in low wind speed periods, when the wind turbine is still not running, the full reactive power generation capability is available if the converter can be switched solely to the grid.

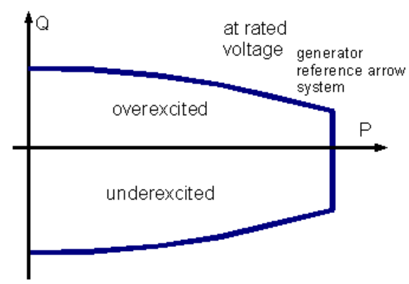

Fig. 2: P-Q-characteristic of an exemplary DFIG

C. Grid Requirements

When a wind farm is connected to the high voltage or even ultra-high voltage grid, it has to fulfill the same requirements as every conventional power plant does. The transmission system operators (TSO) define such requirements in their grid codes for the respective voltage levels. These grid codes, which depend on the structure of the TSO's grid, can differ from company to company even if they are located in the same country.

The power factor requirements during the normal operation of two German TSOs [5] are illustrated in Fig. 3. There is a clear difference between the Fig. 3(a) and Fig. 3(b). These are proposed by TSOs and depend on the network, load and geographical conditions, etc. In Fig. 3(b), the whole operating range seems to be moved to the under-excited area. The reason may be low-load and reactive power surplus situations. Thus, the generating units need to operate in under-excited mode for limiting the voltage. Other TSO prefers to operate the generators in overexcited mode to support the grid voltage. This may be necessary if the TSO's grid is heavily loaded or supplies a huge reactive power loads.

If a transformer, which connects the wind energy system to the grid, is equipped with an OLTC, the voltage on the secondary side can be changed for the optimal operation of the wind generators.

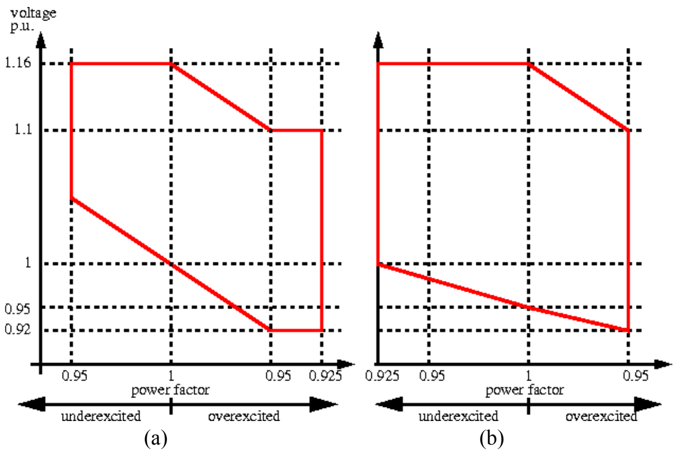

Fig. 3: Power-factor requirements of two TSO for generating units connected to the high voltage grid

III. Particle Swarm Optimization

Particle swarm optimization (PSO) [6]-[7] is an evolutionary computational technique developed by Kennedy and Eberhart. Unlike the other population based search algorithms, PSO finds the optimal solution not by survival of the fittest but by a process motivated by the simulation of social behavior such as fish schooling and birds flocking in search of food. PSO algorithm is initialized by a population of random potential solutions called particles and the group of particles is called a swarm. Each particle in the swarm moves over the search space with a certain velocity. The velocity of each particle is influenced by the particles' own flying experience as well as its neighbors' flying experience. PSO solves a highly constrained problem as an unconstrained one by adding a suitable penalty function to the main objective function.

A. Adaptive Particle Swarm Optimization: A 'Tribe' Concept

Adaptive particle swarm optimization (APSO) [13] is a parameter free technique. The significant feature of this algorithm is that the optimization algorithm can be used as a black box where only the search space, the objective function to be minimized, and a stopping criterion for the algorithm are to be given. The algorithm is totally free from parameter tuning and also from the burden of selecting the most appropriate swarm (population) size. In this algorithm, different sized groups of particles, called "*Tribes*", move in the search space to find a local minimum. Information linkages exist among the particles of a tribe. Each such tribe succeeds in finding a local minimum. Information linkages also exist among the different tribes, as shown in Fig. 4, through which they exchange information regarding their local minimums to collectively decide the global minimum.

These information structures are automatically generated and updated by means of creation, evolution and deletion of particles and tribes. Based on the performance of particles and swarm, different strategies of displacement are selected. Each particle in the swarm memorizes two previous performances. The performances can be an improvement (+), status quo (=) or a deterioration (**-**). A particle is considered excellent if its previous two performances are improvements (++), good if it has just improved its performance (= +) and neutral, if neither of the previous two performances are improved (= =). The performance of a tribe is judged based on its particles. A tribe is good if it has more number of good particles and otherwise, it is bad.

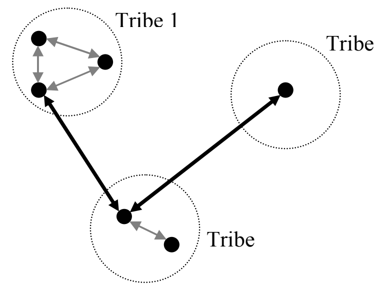

Fig. 4. Tribes of different sizes and the information linkages

The main objective of APSO is to find the optimum solution with few function evaluations. So, whenever there is a chance of deleting a particle with almost no risk is encountered, we must take it. It is considered better to preserve a worst particle which, by mistake, leads to more function evaluations than to remove one by mistake which might lead to the risk of completely missing the solution. So a good tribe will identify its worst particle and remove it because it doesn't carry any useful information. On the other hand a bad tribe needs more information for none of its particles seems to converge. So the bad tribe will identify its best particle and this particle will generate a new particle. Each bad tribe will generate one particle, simultaneously, and these new particles will form a new tribe. These adaptations take place when the number of iterations is greater than half the information links since the last adaptation.

Different particles have different moving strategies as shown in Table I. A bad particle (= =, = –) requires a global search and hence nonlinear moving strategy is used. The rest of the particles follow the standard linearly decreasing weight method. These strategies are explained below.

TABLE I
DISPLACEMENT STRATEGY FOR DIFFERENT PARTICLES

Particle Performance	Displacement Strategy
(– –)(= –)(– =)(= =)	Nonlinear method
(+=)(= +)(+ +)	linearly decreasing weight method

B. Standard Linearly Decreasing Weight Method

In this displacement strategy, the particles' positions are updated by adding a dynamic velocity. The velocity of each particle depends on three terms. The first term is the inertia velocity which carries information regarding the particles previous history of velocities. The second term is the cognitive part which reflects the particles behaviour with respect to its own previous experiences. The final term is a social parameter which indicates the particles behaviour with respect to the experience gained from the other members of the swarm. This velocity ($v_{jk}(t+1)$) when added to the previous position ($x_{jk}(t)$) generates the current position ($x_{jk}(t+1)$) of the particle-j as given by the following equations.

$$v_{jk}(t+1)=\chi(wv_{jk}(t)+c_1r_1(p_{bk}-x_{jk})+c_2r_2(p_{gk}-x_{jk})) \quad (1)$$

$$x_{jk}(t+1)=x_{jk}(t)+v_{jk}(t+1), \qquad \forall j\in N_p, k\in n \quad (2)$$

where $\phi = c_1r_1 + c_2r_2$ and

$$\chi=\begin{cases}\dfrac{2a_1}{\phi-2+\sqrt{\phi^2-4\phi}}, \phi>4\\ a_1, otherwise\end{cases} \quad (3)$$

where c_1 and c_2 are the fixed acceleration coefficients, r_1 and $r_2\in[0,1]$, χ is the constriction factor, a_1 is a positive constant, p_{bk} and p_{gk} are the particles individual best and the best particle in the swarm, respectively. N_p is the set of all particles in the swarm and n is the dimension of the search space. The weighing factor (w) for previous velocities is considered to be a linearly decreasing function so that it provides a good trade off between local and global explorations.

C. Nonlinear Method

In this strategy, particles move in a region defined on the global best particle and the individual best. The particles move far away from the current position. Global exploration is done using this strategy. Another advantage of this strategy is that it avoids the possibility of premature convergence. When $x_{jk}=p_{bk}=p_{gk}$, the velocity of the particle is zero. The particle can no longer move from its current position and will, therefore, converge on its current position which might not even be a local minimum. To avoid such a situation, a region is defined around the particle and velocity is randomly generated within this region. The update equation below of particle-j is a simplified version of the standard form (1).

$$x_{jk}(t+1)=x_{jk}(t)+wv_{jk}(t)+\varphi(p_{qk}-x_{jk}(t)) \quad (4)$$

$$p_{qk}=f(p_{bk},p_{gk}) \quad (5)$$

Function $f(p_{bk},p_{gk})$ gives a positive Lebesgue measure [14] by defining a dynamic ellipse E having focuses at p_b and p_g, and ρ is the distance between p_b and p_g. The equation of ellipse can be given as

$$\frac{(X-M)^2}{a^2}+\frac{(Y-N)^2}{b^2}=1 \quad (6)$$

$$\rho=\sqrt{\sum_{k=1}^{n}\left(p_{gk}-p_{bk}\right)^2} \quad (7)$$

$$N=M=[m_1,m_2....,m_n]=\frac{p_b+p_g}{2} \quad (8)$$

$$b=\sqrt{\sum_{k=1}^{n}\left(m_k-p_{sk}\right)^2}, a=\sqrt{b^2+\rho^2} \quad (9)$$

p_{sk} is a randomly selected particle from the swarm. Once the ellipse is defined, vector p_{qk} is calculated as follows

$$p_{qk}=\begin{cases}m_k+a\cos\theta, & \text{if}(random<p_d)\\ m_k+b\sin\theta, & \text{otherwise}\end{cases} \quad (10)$$

where, θ is randomly selected, p_d is a bound and $random\in[0,1]$

IV. PROBLEM FORMULATION

A. Reactive Power Management Problem

The optimal management of VAr sources in a wind farm is an optimization task which can be divided into two stages: before installation of the wind farm (planning stage) and continuously during service (operation). The optimization algorithm can be used to calculate several scenarios in the planning stage [15]. During the operation of wind farm, an optimization algorithm is used for efficient operation of the system as per grid requirements. It will optimize power flow with regard to the system losses of the wind energy system and gives the set points of the equipment that the operator needs to control. Some of the VAr sources, which can provide minimum loss, if operated optimally, can be varied continuously while others allow variation only stepwise so that the task which has to be solved represents a mixed-integer optimization problem. The real power loss in the system (P_{loss}) is a function of the control and dependent variables. The control variables are:

- The transformer tap change ratio ($t_{Tr,k}$),
- The wind turbine VAr settings (Q_{WT}),
- The switchable cable (n),
- Switched reactor/capacitors (X_T/X_c) and
- VAR compensator (SVC) settings (Q_{svc}).

These variables have their upper and lower limits. Changes in these variables affect the distribution of the reactive power and therefore the voltage profile and current distribution within the grid. The dependent variables are:

- The reactive power outputs of other generators (Q_g),
- The voltage magnitude of the buses other than the PV buses (U).
- Current through the cables, lines and transformers (I)

These variables also have their upper and lower limits. In mathematical form, the problem, in general, can be expressed as

$$\text{Minimize } P_{loss}(x, b) \quad (11)$$

Subject to

$$b_{\min} \le b(x) \le b_{\max} \quad (12)$$

and

$$x_{\min} \le x \le x_{\max} \quad (13)$$

where, b is the vector of dependent variables, x is the vector of the control variables, $b_{\max}$ and $b_{\min}$ are the upper and lower limits on the dependent variables, and $x_{\max}$ and $x_{\min}$ are the upper and lower limits on the control variables.

In this work, reactive power generation of wind farms (continuous variable), transformer tap changers' position (discrete variable) along with cable switching (discrete variable) have been considered for wind farms' VAr management. This is a mixed-integer nonlinear optimization problem which is solved using the proposed adaptive particle swarm optimization technique. The problem is formulated in a general way so that any other available reactive power sources (discrete or continuous) such as bus or tertiary reactors, SVC or STATCOM etc. can be easily incorporated.

B. Solution Algorithm

The constrained problem as defined in (11)-(13) is solved using APSO as an unconstrained problem by using a penalty function [16] approach. The objective function is the sum of the distance value, d(x) and the penalty value, p(x).

$$\text{Minimize } d(x)+p(x) \tag{14}$$

The distance value is defined as follows

$$d(x)=\begin{cases} b'(x) & \text{if } r_f=0 \\ \sqrt{P'_{loss}(x,b)^2+b'(x)^2} & \text{otherwise} \end{cases} \tag{15}$$

where

$$r_f=\frac{number\ of\ \ feasible\ particle}{swarm\ size}$$

$P'_{loss}(x,b)$ is the normalized power losses and b'(x) is the sum of the normalized violation of each constraint divided by the total number of constraints. When there are no feasible particles in the swarm, the distance value is equal to the constraint violation b'(x). Now the objective function is to reduce the constraint violation, hence the particles are pushed to the feasible space. When there are feasible particles in the swarm the distance value is the root mean square sum of the constraint violation and fitness value (15). This definition will give higher fitness value to infeasible particles. The performance of the optimization algorithm can be improved if the information carried by the infeasible particles is taken into account. During the early stages of the search procedure when the number of feasible particles is low, infeasible particles with low constraint violation carry more information. Towards the end of the process, when there are more feasible particles, infeasible particles with low objective value can help in obtaining a better optimal solution. So, different sets of infeasible particles are useful at different stages of the optimization process. This technique is implemented by the penalty term, p(x) in (14) as follows:

$$p(x)=(1-r_f)X(x)+r_f Y(x) \tag{16}$$

where

$$X(x)=\begin{cases} 0, & \text{if } r_f=0 \\ b'(x), & \text{otherwise} \end{cases}$$

$$Y(x)=\begin{cases} 0, & for \text{ feasible particles} \\ b'(x), & for \text{ infeasible particles} \end{cases}$$

The binary variables (cable switching) are handled using sigmoid function and is defined as follows:

$$sig(v_{jk}(t+1))=\frac{1}{1+\exp(-v_{jk}(t+1))} \tag{17}$$

If k[th] dimension of the j[th] particle happens to be a binary variable, then a probability threshold $sig(v_{jk})$ is defined in the range [0.0 1.0] using (17). This threshold is then compared with a random number *rand( )* drawn from a uniform distribution between 0.0 and 1.0. The current position $x_{jk}(t)$ is updated as follows:

if $sig(v_{jk}(t+1)) > rand( )$, then $x_{jk}(t+1) = 1$
else $x_{jk}(t+1) = 0$

The discrete variables such as transformer tap changer's position is normalized and converted to integers (0,…,n). Where n corresponds to the number of tap changing positions. The velocity of the discrete variable calculated from its corresponding velocity update equation is rounded of to its nearest integer.

The optimization process starts with a random generation of a single particle corresponding to the set of variables within the admissible range representing a single tribe. The particle then enters the inner loop where a fitness value is assigned. Initially the load flow is performed. If load flow doesn't converge the objective is 2.5 times the loss corresponding to the individual best of the particle (loss (p_b)). In such a way it is ensured that the algorithm will always move away from the infeasible solutions.

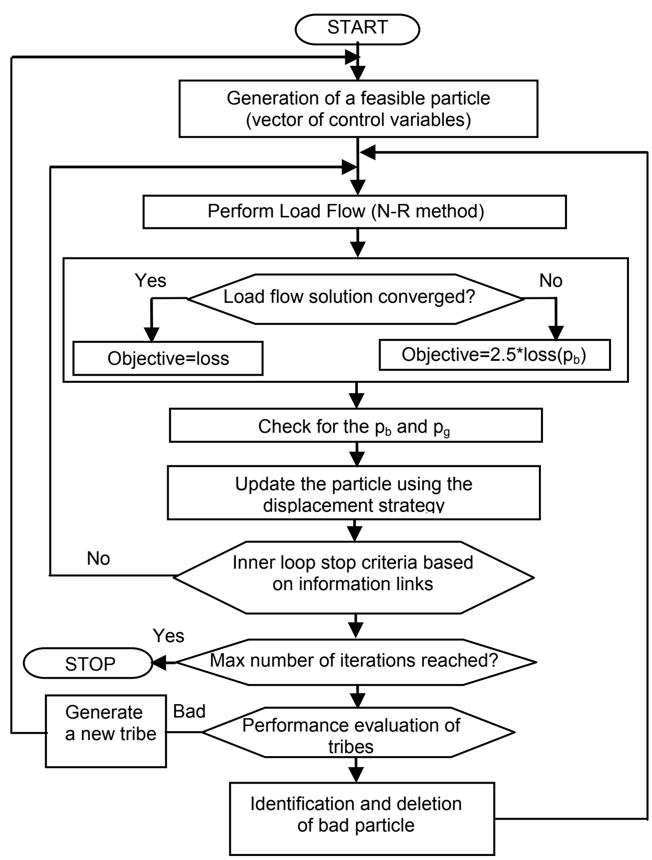

Fig. 5. Flowchart of adaptive particle swarm approach

The load flow is performed using Newton-Rampson method without any simplification. The operating constraints are checked and a penalty is added for each violation. The fitness value of the particle is given by (14). In the next step, vectors p_b and p_g are evaluated. Initially these vectors are set to the current searching point.

In the following step the position of the particle is updated based on its corresponding displacement strategy as listed in Table I. The inner loop is checked for the termination condition. The termination criterion is usually half the number of information links since the last adaptation. Outside the inner loop, the tribe is evaluated. During these evaluations either a new tribe is added or an existing particle is deleted based on the performance of the existing tribes. The outer loop is executed until the stopping criterion, which is usually the maximum number of function evaluations, is met. Flow chart of the proposed approach for reactive power management is shown in Fig. 5.

V. Results and Discussions

The effectiveness of the proposed adaptive particle swarm optimization is tested on a German offshore wind park as shown in Fig.1 having 80 wind turbines each rated at 5 MW, 0.95 kV, connected to the main grid (380 kV) with two, 144 km long cables (94 km AC submarine cable and 50 km onshore cable) each rated at 150 kV. Two step-up transformer of rating 36 kV/150 kV and 150kV/380kV with on-load tap changing facility are used as shown in Fig. 1. For demonstrating the optimization algorithm the total generation is taken as 40 MW which is 10% of rated wind farm power output (P_N=400 MW). This generation is taken to show the effectiveness of cable switching (during normal loading both cables are in operation).

The minimal loss of the wind energy system is obtained by running the APSO for the offshore wind park consisting of 195 nodes, 4 shunt elements, 97 single lines, 3 three-winding transformers and 80 DFIGs with their machine transformers. For simplicity reasons, the reactive power of all generators of the wind park is kept equal. Under low generation conditions, a single cable is capable of carrying the generated power from the wind park to the grid. Thus, switching of cable is also considered as one of the optimization variables along with the tap changing transformer positions and reactive power generation of the wind turbines.

Adaptive PSO as suggested in section III is used to obtain the operational settings of the wind energy system providing the minimum losses. Fig. 6-10 shows the power losses, reactive power, cable switching and tap changer ratio for all iteration steps of the optimization process for 0.1 p.u. generator output. Table II gives a short overview of the best results obtained for 10% to 100% of rated power.

The real power loss obtained in the different iterations of PSO is shown in Fig. 6. It can be seen that minimum real power loss is found to be 1.6152 MW (at 10% of rated output of wind power) in 1500 iterations. The convergence is very fast. Each run of the optimization algorithm (1500 iteration steps) takes about 3.36 seconds on a P4 with 3.4 GHz. Figure 6 shows the best value found so far (solid line) and the current value (point) of each iteration step. The current values below the solid line are the results of the load flow with constraint violations. Thus, these results are considered as infeasible. The reactive power generation of a single wind turbine during the iteration process of PSO is shown in Fig. 7. The switching of cable is also crucial in the reactive power management for required grid code where power factor at the point of common coupling is to be maintained in the desired limit. Fig. 8 shows the status of cable-2 during the optimization process.

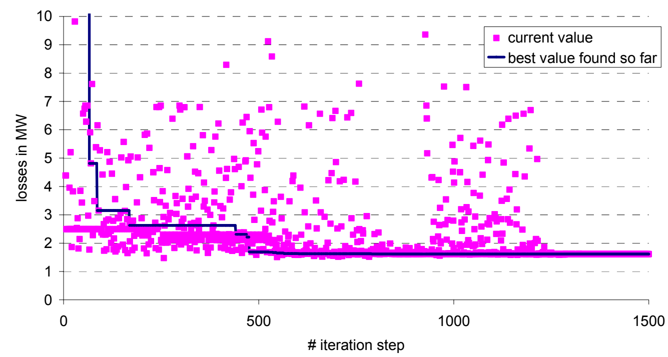

Fig. 6. Minimum wind energy system loss during the APSO iterations

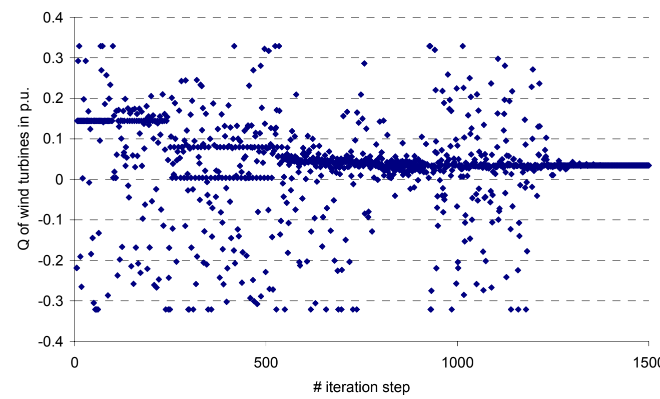

Fig. 7. Reactive power generation of a single wind generator during the APSSO iterations

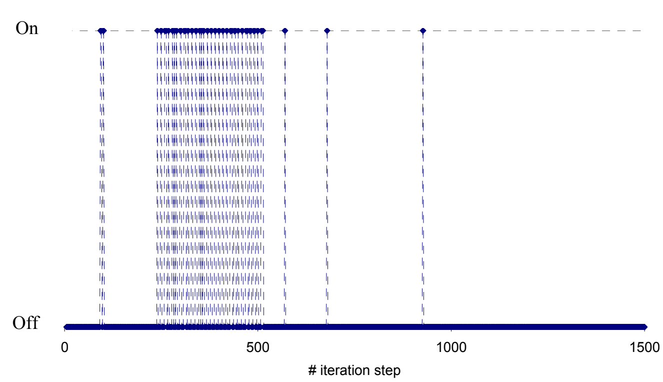

Fig. 8. Cable-2 status during the APSSO iterations

The optimal settings of transformer taps are shown in Fig. 9 and Fig. 10. Fig. 9 shows the tap set points of 36/150 kV transformer whereas Fig. 10 shows the tap set points of 150/380 kV transformer. To demonstrate the effectiveness of the APSO, the generated power output of the wind farm is varied and the results are shown in Table II.

Fig. 9. Tap changer set pint of 36/150 kV transformer during the APSSO iterations

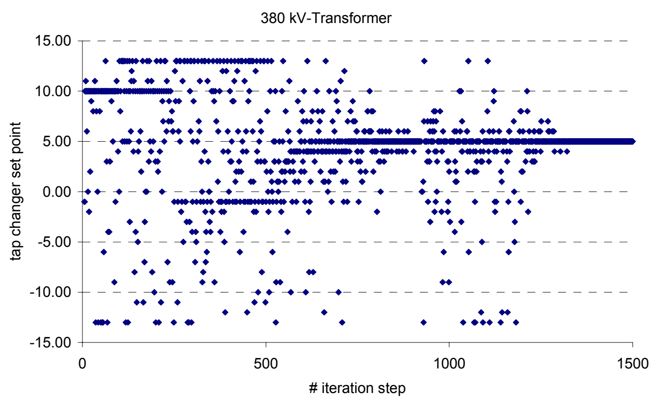

Fig. 10. Tap changer set point of 150/380 kV Transformer during the APSSO iterations

TABLE II
REAL POWER LOSS AND OPTIMAL PARAMETER FOR DIFFERENT LOADING

P_{WT} (MW) (% of P_N)	P_L (MW)	Q_{WT} (Mvar)	Transform tap settings (36/150)	(150/380)	Cable-2 status
40.0 (10%)	1.6152	0.1800	6	5	OFF
80.0 (20%)	2.8264	0.1445	12	0	OFF
160.0 (40%)	5.6857	0.2817	3	1	ON
240.0 (60%)	10.1757	0.0649	4	1	ON
320.0 (80%)	16.4876	-0.1027	5	0	ON
400.0 (100%)	24.6559	-0.3921	6	-1	ON

VI. CONCLUSION

This paper proposes a new adaptive particle swarm optimization (APSO) technique for solving optimal reactive power dispatch problems to achieve minimum real power loss in a grid connected offshore wind farm. The APSO is free from tuning of population size and is based on different sized groups of particles called "Tribes". The simulation results show the robustness of the algorithm in terms of getting the optimal solution of a mixed integer, nonlinear optimization problem. It is recommended to implement and run the algorithms in online mode as part of the wind farm management software so that the setting are always adapted when the wind conditions as well as the grid requirements change. A proper operation of reactive power sources in the wind farms will give a better economy. This paper could be a guideline for policy makers and system operators to promote wind power in terms of system reliability and security.

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