Reactive power management in Wind Farms using PSO technique

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Abstract. This paper presents a particle swarm optimization (PSO) technique for a reactive power wind farm (WF) dispatch function, in order to calculate the reactive power reference for each wind turbine (WT). The dispatch can be formulated as the problem of minimize the difference in power interchange at interconnection point (PCC). Incorporation of PSO as a optimization technique for the WF dispatch make possible consider different parameters to improve it performance and give it more capabilities.

Key words

Wind farm, reactive power control, wind farm control, particle swarm optimization.

1 Introduction

Nowadays the amount of wind power have been reached important penetration percentage in power systems. With this growth, the power systems has greater control necessities, that means the wind farms (WF) has to meet this control needs, mainly voltage or reactive power control and frequency control.

Therefore the Transmission System Operators (TSO) in different countries have been working for integrate in their grid codes control requirements for WF [11], [2], [9]. The reactive power control have to be done by the WF with the aim of fulfill with the principal issues of voltage control required by TSOs. The principal functions of the WF control are follow the reactive power set point at connection point (PCC). Dispatching of aero-generators of the park should be done in order to improve power production and reduction of electrical losses, taking into account the operating capacities of WF.

The need of optimize the generation has been studied for different purposes and using several methods. The problem of reactive power control flow problems and network capacity analysis [8], [12] have been treated with optimization techniques.

Since the end of the twentieth century new optimization technique has been studied, using analogy of swarm behavior of animals. In [1] ant colony optimization was developed. Eberhart and Kennedy developed particle swarm optimization (PSO) based on the swarms behavior of birds or fish [6]. This new technique has been used in power system controls recently and for reactive power and voltage control [4].

The problem of reactive dispatch between the single aero-generators of a WF is formulated as an optimization problem subject to restrictions. The principal objective function is minimize the starting error between WF reactive power generation and TSO requirement using Particle swarm optimization (PSO) technique.

PSO is a evolutionary computation technique. This technique apply social psychology principles in socio-cognition human agents. And it has been motivated by the behavior of organisms that act as a block, for example a fish schooling and a bird flocking. PSO is based on the computational representation of a swarm of birds. The behaviour of the birds is act as a group to seek food, its objective for example. Therefore each individual (agent) reconfigure its behave based on its own experience and its neighbors experience.

Each searching point is an agent. Basically the position of each agent is represented in a two dimension space and for each dimension there is a associated velocity. This velocity is in charge to move the agents.

Each agent knows its best historical value and the corresponding position. Besides each agent knows the value and corresponding position of the best agent of the swarm. This information is an analogy of the knowledge of the other agents around them have performed. Each agent tries to change its position using this information and the velocity.

2 Particle Swarm optimisation technique

Particle swarm optimisation (PSO) is an evolutionary computation technique that applies an analogy of swarm behaviour of natural creatures. It has been motivated by the behaviour of organisms acting as a unit, for example the schooling of fish and the flocking of birds. Birds usually seek food (their objective) in swarms. Each individual bird (agent) reconfigures its behaviour, based on its own experience and the experiences of others.

Then, from an OF (1), where the aim is to optimise the steady performance of the system, PSO uses multiple searching points (each searching point is an agent), in the process to find the optimal solution [7].

$$Minimise J(x,y) \tag{1}$$

Where x denotes the dependent variables, consisting in bus voltages, transmission line loadings, etc. and where y denotes the independent variables, in this case WT reactive power consumption/generation.

Basically, the position of each agent has an associated velocity v_i^k, this is responsible for the movement and the position change of the agents.

Each agent knows its best historical value and the corresponding position. In addition, each agent is aware of the value and corresponding position of the best agent of the swarm. This information is an analogy of the knowledge of the other agents around them. Each agent tries to change its position, using the current position s_i^k and the velocity for the next iteration v_i^{k+1}. The position of an agent for the next iteration is

$$s_i^{k+1} = s_i^k + v_i^{k+1} \tag{2}$$

and the velocity of each agent has also to be modified as follows,

$$v_i^{k+1} = wv_i^k + c_1 r_1 \times (p_{best-i} - s_i^k) + c_2 r_2 \times (g_{best} - s_i^k) \tag{3}$$

and is usually limited to a certain maximum value where:

- v_i^k: velocity of agent i at iteration k
- w: inertia weight function
- c_1, c_2: positive weighting constants
- r_1, r_2: random number between 0-1
- s_i^k: current position of agent i at iteration k
- p_{best-i}: individual best of agent i
- g_{best}: best of the group

The weight function provides a balance between global and local explorations. It is defined to decrease linearly from a maximum value $w_{max} = 0.9$ to a minimum value $w_{min} = 0.4$ during the searching process. There are different possible weight functions w, the most commonly used is [10]

$$w = w_{max} - \frac{w_{max} - w_{min}}{k_{max}} \tag{4}$$

The general concept of PSO can be seen in figure 1.

3 Problem formulation and tested WF

The voltage control problem in WFs could be solved with the own production or reactive power of the WTs. The proposed algorithm seeks to optimise the reactive dispatch between the WTs with the aim to achieve the requirement voltage or reactive control of TSO at PCC. The problem can be formulated by a principal OF

$$Minimise J(x,y) = |Q_{PCC}^{*} - Q_{PCC}^{meas}| \tag{5}$$

where Q_{PCC}^{*} is the reactive power required in PCC by the TSO, Q_{PCC}^{meas} is the real reactive power generated by the WF and measured at the PCC. The result of the proposed algorithm is the reactive power set point for each WT.

The OF (5) is subject to power flow constraints, WT reactive power lower and upper limits (6), security voltage constraints for the N_B bus bars and current constraints for the N_L lines.

$$Q_{WT}^{min} \leq Q_{WTi} \leq Q_{WT}^{max}, i = 1, ..., N_G \tag{6}$$

Each particle or agent X_i^k is a candidate solution, represented by a m-dimensional vector, where m is the number of optimised parameters, in this case the reactive power of each WT. Therefore, there are A agents, each one is a vector in which the dimensions represent the reactive power of a single WT.

The initial searching points are randomly generated between the space of possible values $[Q_{WT}^{min}, Q_{WT}^{max}]$. Once the values are updated, the load flow executed and the OF evaluated, the g_{best} is selected. Then, a new velocity is calculated and new positions are fixed. After that, load flow is executed, the OF evaluated and individual best p_{best} updated. Finally, g_{best} is determined and stop criterion evaluated, as can be seen in Fig. 1.

In this way, the optimal solution will be the values of the WT's reactive power generation which satisfy the TSO requirement. The first method studied has the optimal reactive dispatch as the OF (5), however multiple optimal functions are studied. The alternative OF includes the minimisation of losses along the branches of the WF (7).

$$Minimise J(x,y) = |Q_{PCC}^{*} - Q_{PCC}^{meas}| + \lambda \sum_{i=1}^{N_L} P_{Loss-i} \tag{7}$$

where N_L is the number of lines in the WF, and λ is a relative weight used to study the objective combination of reactive dispatch and power losses. The use of weights has been described as one of the most widely used methods for multi-objective (MO) optimization problems [5, 3]. Although exist other methods for the study of MO problems, the weighting method is here applied owing to its simple implementation. Weighting method permits treat a MO function as a single-objective function and has been identified as one of the most applied in power system applications [7].

The proposed dispatch method has been tested on the WF shown in Fig. 2. The external grid has a short circuit power of 400MVA. The line data is presented in Table 1. The WF has 12 WTs connected, as seen in the sketch. The WT has a nominal power of 2.0 MW and is represented by a PQ model. The WT transformers are $0.69/20kV$, $2.5MW$ and the PCC transformer is $20/132kV$, $26MW$.

Table 1: Line data for WF tested

Line	Longitude	R [Ω]	X [Ω]
Line1	1 km	0.134	0.383
Line2	1.5 km	0.042	0.174
LineAG1	0.3 km	0.096	0.035
LineAG2	0.4 km	0.128	0.046
LineAG3	0.4 km	0.128	0.046
LineAG4	0.5 km	0.16	0.058
LineAG5	0.3 km	0.096	0.035
LineAG6	0.4 km	0.128	0.046
LineAG7	0.4 km	0.128	0.046
LineAG8	0.5 km	0.16	0.058
LineAG9	0.3 km	0.096	0.035
LineAG10	0.4 km	0.128	0.046
LineAG11	0.4 km	0.128	0.046
LineAG12	0.5 km	0.16	0.058

The algorithm was implemented in DIgSILENT, using the DPL (DIgSILENT Programming Language). In this implementation, the number of agents A is 20, constants values are $c_1 = 2.0$, $c_2 = 2.0$, and the stop criterion is the maximum number of iterations reached, in this case 100.

4 Results

Three different methods to do the reactive power dispatch are tested and compared.

- Method 1. The setting point at PCC is proportionally distributed between the WTs of the WF.
- Method 2. The dispatch was made by the proposed PSO algorithm, where the OF is to minimise the differences between set point and the exchange of reactive power at PCC, as shown in equation (5).
- Method 3. An alternative two-fold OF for a PSO algorithm is applied, with the aim to minimize the losses along the WF lines, by the objective function as shown in equation (7). Four variations are tested:
  - Variation 1. λ=1
  - Variation 2. λ=0.7

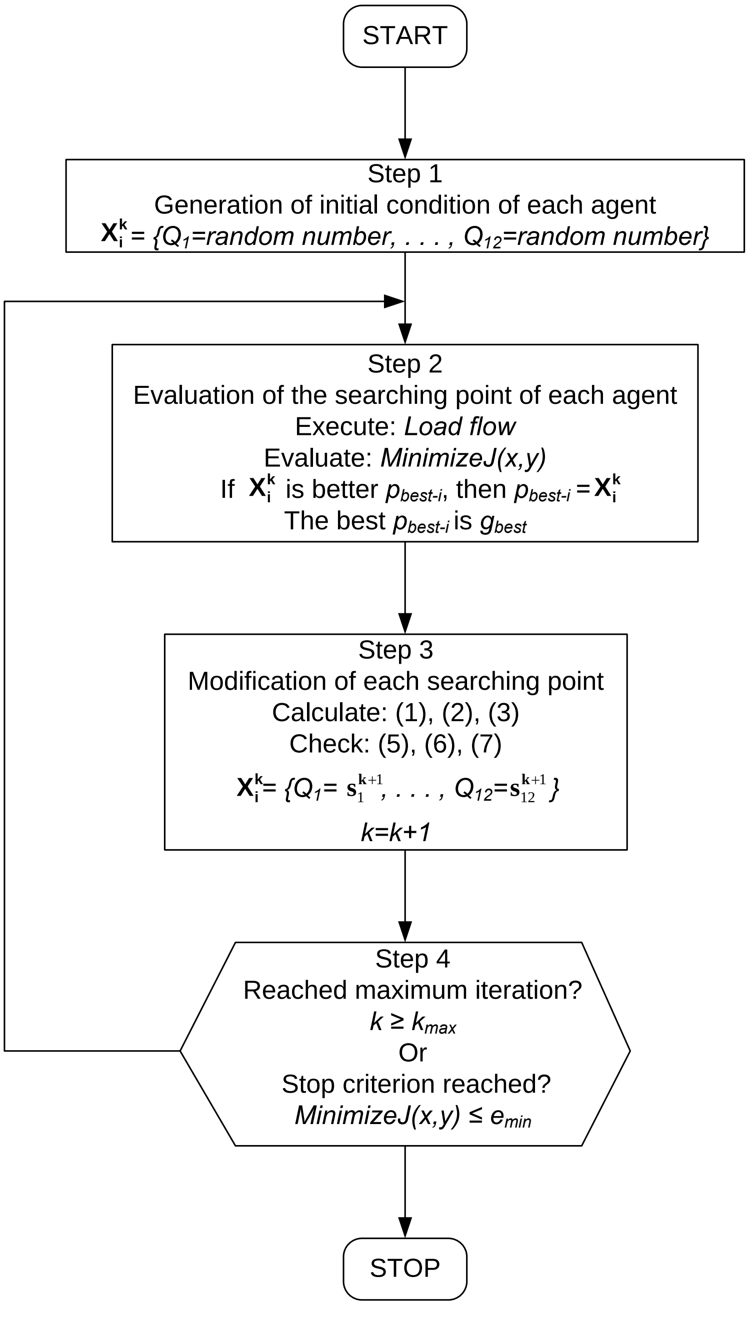

Figure 1: Flow chart of proposed PSO algorithm

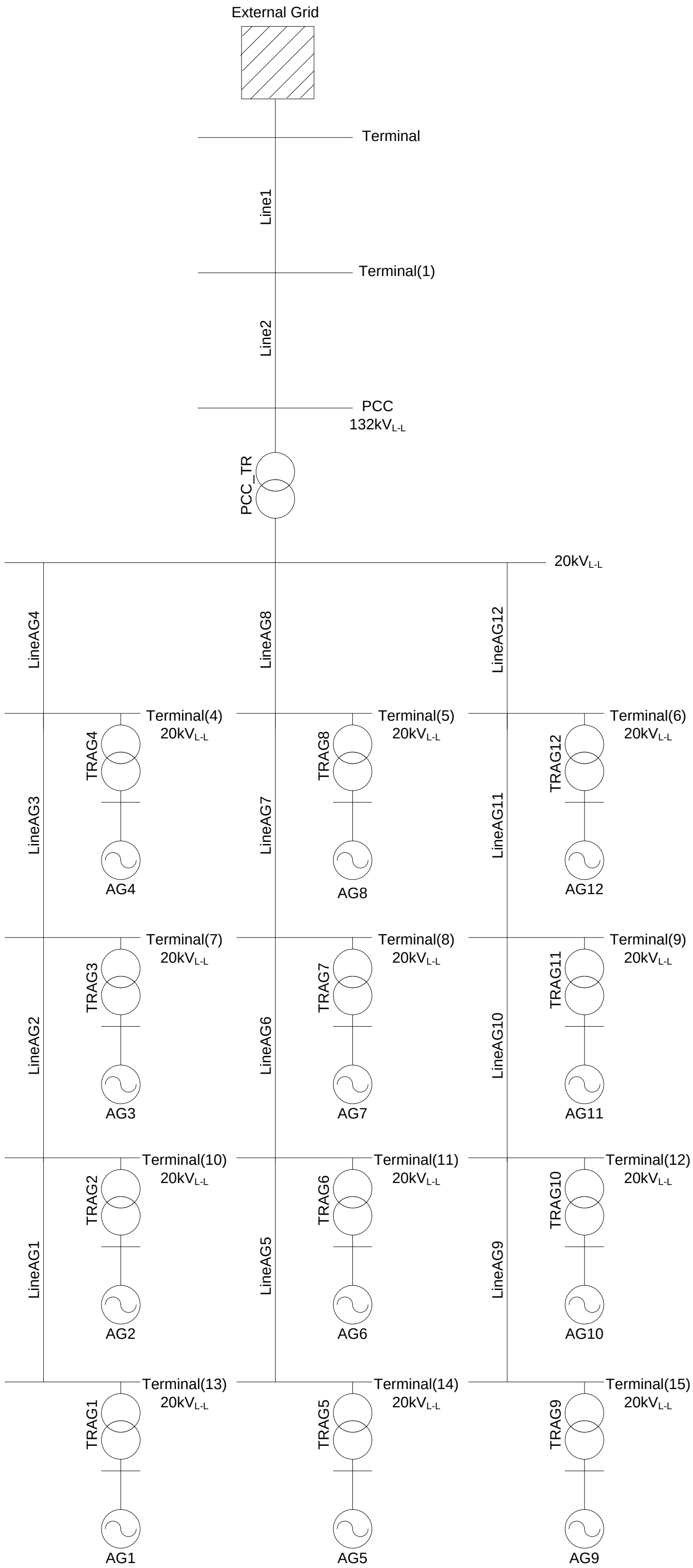

Figure 2: Layout of the tested wind farm

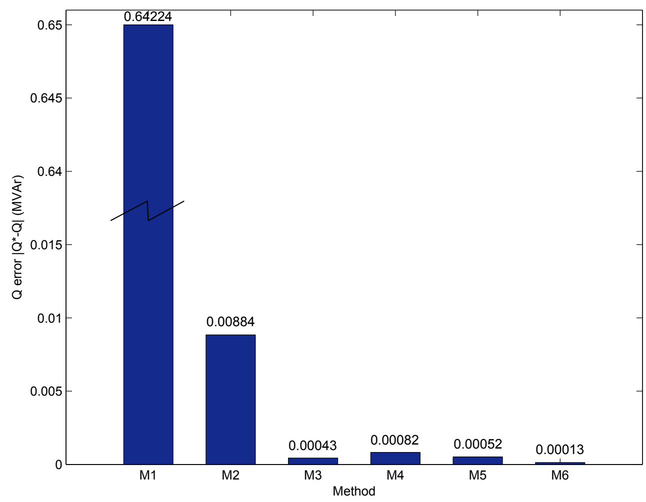

Figure 3: Error in reactive power at PCC for each method.

- Variation 3. λ=0.5
- Variation 4. λ=0.3

The WTs are operating at 90% of its nominal power, so the operation point of the WF is 21.6MW, for the reactive power the set point for all methods is 4.8MVAr, this value could be fixed or determined since the grid code requirements for the voltage or reactive power control.

the voltages for the bus bars are in between the operative margins. The highest voltage can been observed for BAG5 with M3 is 1.0482 pu ($\lambda = 1$), the voltage for the same bus with M1 is 1.0422 pu; this voltage increment is due to the reactive power injection of WT AG5 in M3.

Table 2 presents the results of reactive power dispatching of each WT for the presented methods. The first two columns, *Min* and *Max*, show the reactive power operation limits for each WT. The comparison of the results of method 1 (proportional dispatching) with PSO methods shows a clear advantage of those methods, optimising the dispatching of reactive power and reducing line losses.

Fig. 3 depicts error in reactive power at the PCC for each method. Method 1 shows the greatest value of error (0.64224 MVAr), which represents an error of 13% between Q^*_{PCC} and Q^{meas}_{PCC}. The dispatch error with method 2 is 0.18%, while the error for the different variations of method 3 is between 0.009% and 0.017%.

In Fig. 4, the losses for all presented methods are summarised. It can be seen that method 1 has the greatest losses (0.11096 MW), in comparison with the other methods. Method 2 allows the reduction of line losses about 0.39% in respect to method 1, even if the OF does not consider the line losses. Nevertheless, when the losses are included in the OF (method 3), a significant reduction of line losses can be achieved. Variations 1 to 4 of method 3 permit a reduction between 6.8% and 7.2% in comparison with method 1. This result clearly shows the usefulness of the proposed algorithm, since it is possible to improve the performance of WFs due to the reduction of losses of the WF and the more accurate tracking of the reactive power set point, provided by the TSO.

Fig. 5 shows the results for the OF (7) for variation 1 to 4 of method 3. It can be seen that the OF decreases until a minimum stable value is reached, and it is reduced as the weight used becomes smaller. The final values for the OF are 0.10351, 0.07309, 0.05196 and 0.03114 for λ 1, 0.7, 0.5 and 0.3, respectively. The maximum number of iterations fixed in this case is 100, the time of simulation is less than two minutes.

Although this method could not be applied in real time for operation in WF, it could be used for the set point calculation of the optimal operation of the WF with specific conditions. This method is not applicable for transients or fast responses. Because in transients the grid codes define a specific response, like for example to give the maximum available reactive power in WTs, then there is not optimization possibilities.

It is clear that by changing the initial values of reactive powers, a completely new solution set would be obtained. The results show the usefulness of the method that could be complemented with any other parameters of the WF and extended to the study of bigger and complex WFs.

5 Conclusions

In this paper, a reactive power dispatch method for a wind farm has been presented, using particle swarm optimisation. Two particle swarm optimisation algorithms were tested with different objective functions in order to optimise

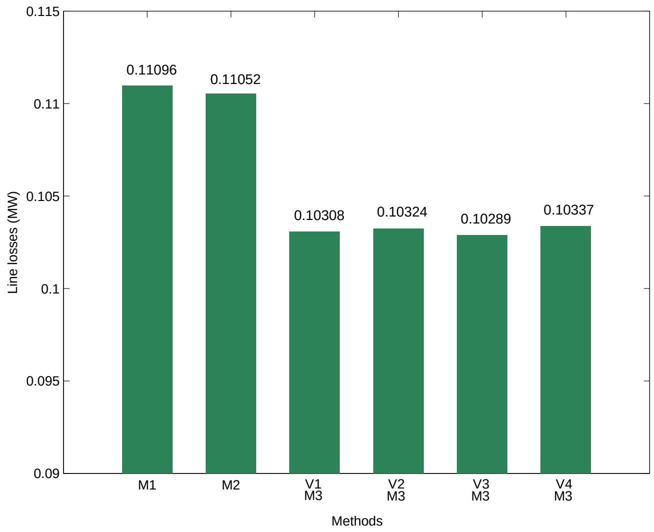

Figure 4: Power losses in WF lines for each method.

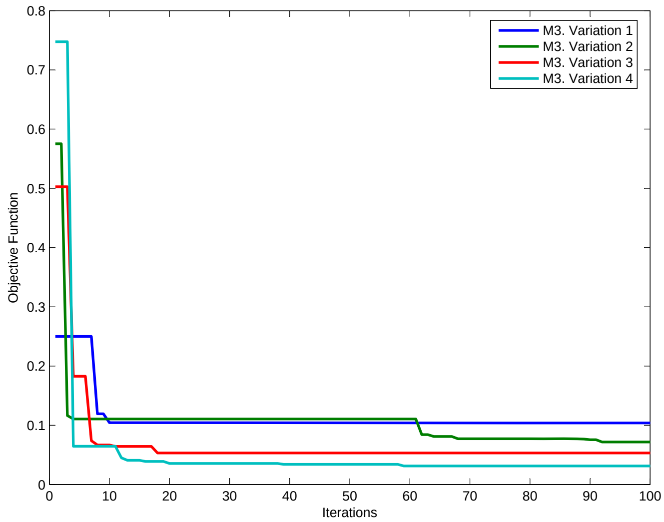

Figure 5: Objective function result variation for methods 3 to 6.

Table 2: Optimal settings of reactive power generations and objective function results

	Min	**Max**	**M 1**	**M 2**	**M 3**			
					$\lambda:1$	$\lambda:0.7$	$\lambda:0.5$	$\lambda:0.3$
Q_1[MVAr]	-0.66	0.66	-0.40000	-0.26037	-0.14178	-0.66000	-0.66000	-0.41219
Q_2[MVAr]	-0.66	0.66	-0.40000	-0.20459	-0.66000	-0.66000	-0.66000	-0.54209
Q_3[MVAr]	-0.66	0.66	-0.40000	-0.35945	-0.66000	-0.20376	-0.14370	-0.04381
Q_4[MVAr]	-0.66	0.66	-0.40000	-0.66000	-0.34104	-0.66000	-0.66000	-0.58383
Q_5[MVAr]	-0.66	0.66	-0.40000	-0.66000	-0.66000	-0.32016	-0.66000	-0.51010
Q_6[MVAr]	-0.66	0.66	-0.40000	-0.38312	-0.66000	-0.66000	-0.26538	-0.39180
Q_7[MVAr]	-0.66	0.66	-0.40000	-0.13075	-0.34411	-0.61857	-0.24345	-0.36273
Q_8[MVAr]	-0.66	0.66	-0.40000	-0.66000	-0.17547	-0.66000	-0.66000	-0.29841
Q_9[MVAr]	-0.66	0.66	-0.40000	-0.66000	-0.66000	-0.05778	-0.66000	-0.66000
Q_{10}[MVAr]	-0.66	0.66	-0.40000	-0.20214	-0.17478	-0.24275	-0.66000	-0.66000
Q_{11}[MVAr]	-0.66	0.66	-0.40000	-0.60986	-0.66000	-0.66000	-0.10835	-0.66000
Q_{12}[MVAr]	-0.66	0.66	-0.40000	-0.66000	-0.32200	-0.06060	-0.08252	-0.33144
OF	-	-	-	0.00884	0.10351	0.07309	0.05196	0.03114
$\lvert Q^* - Q\rvert$	-	-	0.64224	0.00884	0.00043	0.00082	0.00052	0.00013
Line Losses [MW]	-	-	0.11096	0.11052	0.10308	0.10324	0.10289	0.10337
Reduction Losses respect to M1%	-	-	0	0.39295	7.10011	6.95411	7.26955	6.83785

the reactive power dispatch at wind farms and to minimise power losses. The results of the performed simulations were compared with a proportional dispatch method. It was shown that the proposed methods have minor errors in reactive power production in relation to the set point. One of the proposed methods also includes the reduction of line power losses; in this case 7% of loss reduction could be achieved.

The proposed algorithms have been proven to be a useful tool to solve the dispatch problem in wind farms. To find out the set point for the optimum operation of a WF under normal conditions. This method can be implemented in the central control system of a wind farm to improve its performance of reactive power management.

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