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Study of Genetic Algorithm Based Wind Power Integration to Power System

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Abstract – This paper presents a hybrid optimization method that aims at minimizing the total system losses while taking into account the stochastic behavior of Wind Power Generation [WPG] and load during different seasons. One issue related to wind power integration concerns the location and capacities of the wind turbines [WTs] in the network. Although the location of wind turbines is mainly determined by the wind resource and geographic conditions, the location of wind turbines in a power system network may significantly affect the distribution of power flow, power losses, etc. The hybrid optimization method combines the Genetic Algorithm [GA], gradient based constrained nonlinear optimization and the sequential Monte Carlo simulation [MCS] method. The GA is suitable for finding the optimal capacity and location of WTs as both control variables are integer values. The gradient-based constrained nonlinear optimization is adopted for the optimal power factor setting of WTs as the algorithm usually provides the fastest solution.

Keywords:- WPG, WT, GA, MCS, DNO

I Introduction

The connection of large amounts of wind turbines [WTs] to distribution systems presents a number of technical challenges to Distribution Network Operators [DNOs]. These challenges, such as steady-state voltage variation, power losses, voltage stability and reliability, are partly due to the mismatch between the location of energy resources and the local network capability of accommodating the new generation. Particularly, the location of WTs is determined by the local wind resources and geographical conditions. However, the capacity of the existing network where the WTs will be connected may not be sufficient to deliver the generated wind power. As a result, network reinforcement is required, which calls for a high capital investment. System losses, being a major concern for DNOs, may be reduced or increased with the connection of WTs, depending on the locations and capacities of the connected WTs. System losses can be minimized by regulating WTs' power factors or reactive power outputs. This could benefit DNOs by reducing system operation costs without extra investment. Furthermore, DNOs may charge wind power producers for kWh energy flow through their networks by evaluating total network investment and system losses for a time span of 20 years [WTs' life time]. Therefore, a reduction in system losses also benefits wind power producers by reducing their connection fee per kWh.

II Wind Power Model

A. Single Wind Power Model

The model was developed on the basis of one-year wind power data measured from the offshore wind farm with a rated capacity of 165.6 MW. The model is called 'LARIMA' because a limiter is added to a standard autoregressive integrated moving-average [ARIMA] model In a LARIMA(p, d, q) model, p represents the order of an autoregressive [AR] process, q represents the order of a moving average [MA] process, and d represents the degree of differencing operation. The model is shown in Fig. 1.

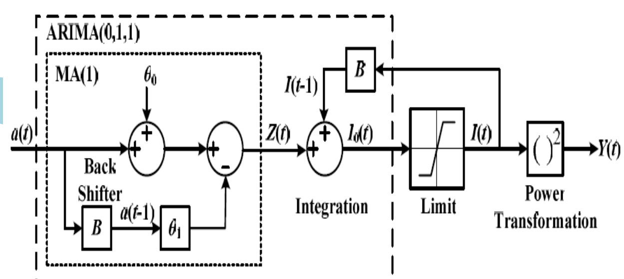

Fig. 1. Single Wind Power Model

B. Wind Power Simulation

The following presents a numerical example of the bivariate-LARIMA model based on the wind power data measured from the wind farm. According to the determined bivariate-LARIMA model, two correlated wind power time series are simulated.wind power data from Part A and Part B of the wind farm are used for parameter estimations. Part A of the wind farm has the same capacity as Part B. In order to account for the seasonal variation, the wind power data are grouped into summer and winter period. For each group of data ($y1(t)$ and $y2(t)$), the square-root and one-degree differencing transformation are applied to obtain two new time series $z1(t)$ and $z2(t)$.

C. Wind Power Time Series Simulation

Bivariate wind power time series, $Y1(t)$ and $Y2(t)$, are simulated according to Fig. 2. The time-domain plot and the scatter plot of the two time series are shown in Fig. 2. $Y1(t)$ is referred to as Wind power A and $Y2(t)$ is referred to as Wind power B. In the actual situation, wind may pass through Part A and Part B of the wind farm at the same time, which results in similar WPG from the two parts of the wind farm; whereas wind may pass from Part A to Part B of the wind farm, which results in different WPG from the two parts of the wind farm. These two consequences are also observed in the simulated time series in Fig. 2(a), where Wind power A and Wind power B have identical values during certain periods and discrepancy during other periods. The time-domain plot also shows that Wind power A fluctuates in a very similar way as Wind power B due to their strong cross-correlation. The strong correlation is also observed in the scatter plot in Fig. 2 (b), whose shape tends to follow a straight line. In addition, the two ends of the scatter plot are more condensed than the middle part. This is caused by the upper and lower limits of WPG due to cut-in and rated wind speed. For comparison, two wind power time series are simulated independently by using the LARIMA model in Fig. 1 for Part A and Part B of the wind farm without taking into account their cross-correlations. The sample probability distribution of the sum of the two uncorrelated time series is shown in Fig. 2 (b). Evidently, the probability distribution is very different from the one shown in Fig. 2 (a). This indicates the importance of correlation modeling when simulating WPG.

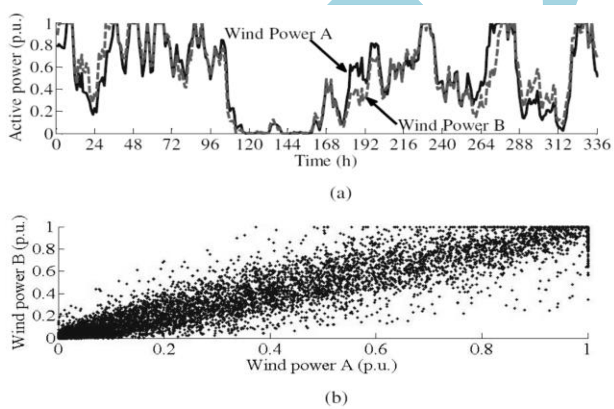

Fig. 2. Wind power (a) time-domain plot, (b) scatter plot

III Optimization Approaches

During the planning stage of a modern distribution system, utilities are interested in knowing the optimal locations and capacity of WTs in the network so that the total system power losses can be minimized during system operation. In addition, the utilities would like to know if the system power losses can be further reduced by controlling the power factor of WTs. However, the utilities usually confront a dilemma that how the stochastic behavior of wind power can be taken into account in a realistic way. The following demonstrates one solution to the issues addressed above.

The presented solution combines standard optimization techniques with sequential Monte Carlo simulation (MCS), which is widely accepted as an effective approach to the analysis of stochastic generation. The hybrid optimization method is graphically illustrated in Fig. 3. The method consists of four parts: 1) load flow calculation for the evaluation of system steady state performance, 2) sequential MCS for the probabilistic assessment of load flow results, 3) constrained nonlinear optimization for the optimal power factor setting of WTs, and 4) GA for the optimal allocation of WTs. The following describes the implementation of the hybrid optimization method in detail.

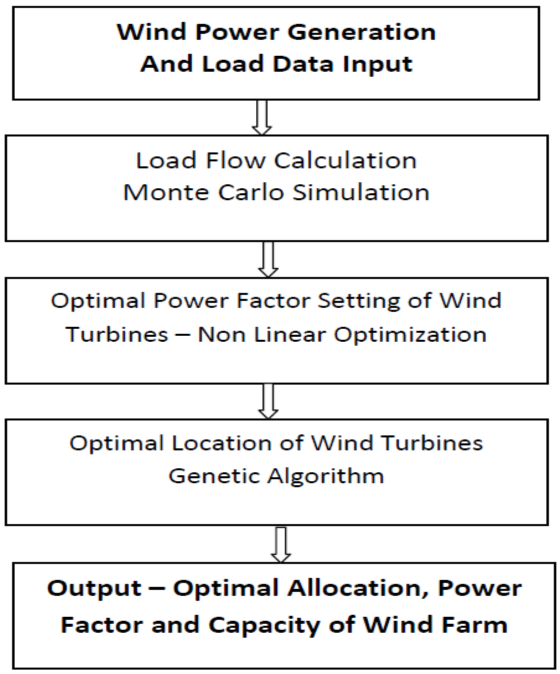

Fig. 3. Hybrid optimization Scheme

A. Optimal Power Factor Setting of Wind Turbines

The constrained nonlinear optimization algorithm aims to minimize total system power losses by controlling the power factor of WTs. The optimization considers the voltage and current limits that are fulfilled at a 95%-probability. As shown in Fig. 3, the optimization requires inputs of total system power losses, bus voltages and line currents from the sequential MCS. The optimization provides outputs of minimum power losses to GA as well as corresponding optimal power factor of WTs. The algorithm for the constrained nonlinear optimization is based on the gradient and Hessian information of the Lagrangian. Mathematically, the objective function of the optimization is to

$$\text{minimize } \overline{P}_{loss} = \frac{1}{N}\sum_{i=1}^{N} P_{loss}(i), \qquad 3.1$$

where N is the length of a MCS, e.g. 8760 for a evaluation over a year; Ploss(i) are the total system power losses at ith hour; Ploss are the average system power losses over the study period. The total system losses are calculated by the sequential MCS shown in Fig. 4. The algorithm performs N consecutive load flow calculations in chronological order. The algorithm requires inputs of power factor of WTs, wind power time series and load time series. The algorithm provides outputs of average system power losses P_{loss} and time series of bus voltages and line currents over the studied period.

B. Genetic Algorithm for Optimal Allocation of Wind Turbines

The GA is used in order to select the types and number of WTs to be allocated at each candidate bus. The GA randomly generates the initial population of solutions (individuals) by defining a set of vectors. Each vector, or called a chromosome, has a size *N N N e C T* = × , where *C N* is the number of candidate locations and *T N* is the number of defined WT types. This is shown in Fig. 4.

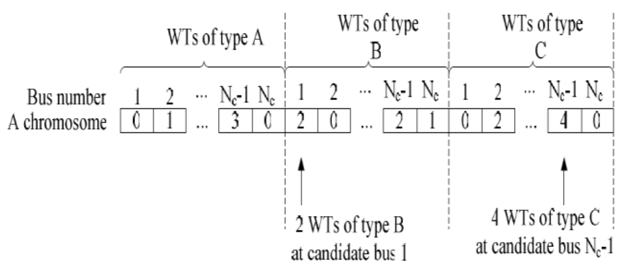

Fig. 4. Schematic of the GA chromosome

As shown in Fig. 4, a chromosome consists of a vector of integers, each of which represents the number of WTs of a given type to be allocated at a candidate bus. For instance, WTs of type A is associated with the first part of the vector with the size of *N*C, which is the number of the candidate locations. Each element of this vector is an integer representing the number of WTs of type A connected to the corresponding bus. As such, the locations and types of WTs are expressed as a string of integers. At each generation of the GA, a new set of improved individuals is created by selecting individuals according to their fitness; the selection mechanism used here is the normalized geometric ranking scheme. After the new population is selected, genetic operators are applied to selected individuals for a discrete number of times. These genetic operators are simple crossover and binary mutation. A simple crossover randomly selects a cut-point dividing each parent into two segments. Then, two segments from different parents are combined to form a new child . A binary mutation changes each of the bits of the parent based on the probability of mutation. An elitism mechanism is also adopted to ensure the best member of the population is not lost. The iteration process continues until one of the stopping criteria is reached.

C. Genetic Algorithm - Monte Carlo Hybrid Optimization Method

For each chromosome of the GA, the constrained nonlinear optimization algorithm nested in the GA algorithm computes the fitness function used by the GA and the optimal power factor setting of WTs. The constrained nonlinear optimization algorithm is based on a sequential MCS, which performs a number of load flow calculations in the chronological order of a year. The sequential MCS generates time series of system power losses, bus voltages and line currents. The system power losses are exported to the constrained nonlinear optimization algorithm as its objective function, with the bus voltages and line currents as its nonlinear constraints. The constrained nonlinear optimization provides outputs of minimum power losses to the GA given a specified number and location of WTs. Consequently, this hybrid method will deliver the best locations as well as the best WT types in the end.

IV SIMULATION STUDY

The 69-bus radial distribution system is used as a case network for the simulation studies. A 12 MVA 33/11 kV substation transformer is included in the network to connect the four main distribution feeders to the slack bus (bus 1). The upper two feeders are located in area A, and the lower two are located in area B. The 11-kV side of the transformer is denoted as bus 70. The voltage at the 11-kV side is controlled at 1.0167 p.u. by a tap regulator. There are in total 13 tap positions, with maximum six steps above and below the reference position. One tap step adjusts voltage by 0.0167 p.u. The voltage limits of all buses are set to ±6% of the nominal value (11 kV), i.e. Vmax = 1.06 p.u. and Vmin = 0.94 p.u. The current limit of all lines is 157A. In this case, the average active power losses of the network without the connection of WTs are 25 kW.

A. Simulation Results

Table 1. The initial values of the number and power factor of WTs for the hybrid optimization method

Bus no.	20 kW	50 kW	100 kW	Total Capacity (kW)	Power Factor
7	2	4	4	640	1.0
15	2	1	3	390	1.0
22	5	1	0	150	1.0
29	5	3	2	450	1.0
38	3	4	4	660	1.0
43	0	0	2	200	1.0
50	3	5	5	810	1.0
56	4	2	4	580	1.0
64	2	2	2	340	1.0

Table 2. The optimal values of the number and power factor of WTs found by the hybrid optimization method

Bus no.	20 kW	50 kW	100 kW	Total Capacity (kW)	Power Factor
7	1	1	1	170	0.91
15	2	0	1	140	0.92
22	0	3	0	150	0.97
29	0	1	2	250	0.80
38	0	1	1	150	0.89
43	0	0	2	200	0.86
50	2	1	1	190	0.80
56	1	0	2	220	0.80
64	4	1	1	230	0.86

Simulation that uses the hybrid optimization algorithm is carried out on the distribution system with wind power and load time series. It is assumed that WTs of three different capacities are chosen by the DNO. These capacities are 20 kW, 50 kW and 100 kW. Maximum five WTs of each type are allowed at a given location. This requirement may be set by the available land for building WTs. For another distribution network with a different load level, WTs with different capacities may be considered. Consequently, GA is used to search for the optimal number of WTs of each type at the candidate locations. It is also assumed that the power factor is the same for all WTs connected to the same bus.

V. CONCLUSION

This paper presents a hybrid optimization method to find the optimal sitting, sizing and power factor setting of WTs in a distribution system in order to minimize the network power losses. The method combines the GA, gradient-based constrained nonlinear optimization and the sequential MCS method, which takes into account the stochastic behavior of WPG and load. The optimization algorithm considers a 95%-probability of fulfilling the bus voltage and line/transformer thermal limits. With this optimization algorithm, a significant reduction of system power losses is achieved as a result of the integration of wind power. Therefore, the described hybrid optimization method can be used to assist the network operators to assess the system performance and to plan future integration of WTs in an effective and practical way.

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