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ANALYSIS OF DISTRIBUTED OPTIMAL ACTIVE AND REACTIVE POWER CONTROL FOR WIND FARMS BASED ON ADMM

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Abstract:

This paper discusses the active power control of a wind farm from a centralized and decentralized perspective. Power coordination between individual wind turbines is monitored and maintained by a central supervisory unit (CSU). To fine-tune the distribution of the farm's output, a power management system has been established within the local supervisory unit. The developed work's primary contribution is the ability to fine-tune the delivered power by each wind turbine via an extra control of the pitch angle. Thus, maximum power point tracking (MPPT) mode and restricted power point tracking (LPPT) mode were considered to establish power control flexibility for the wind farm system. According to the available power in the wind farm, the LSU in each wind turbine's control efficiently coordinates with the power distribution obtained from the CSU. This research presents simulation results demonstrating that the proposed supervision technique for the considered wind farm has good performance and great stability.

Keywords:, MPPT, LPPT, Wind farm, central and local control

1.0 INTRODUCTION

Fossil fuels including petroleum, coal, and natural gas are used to produce the vast majority of today's used energy. Toxic gas emissions and rising pollution levels are direct results of our reliance on these resources. A further risk is that we are depleting our natural resource pool, making it harder for future generations to access this energy. If nothing is done to substantially alter production and consumption, it is predicted that the world's reserves will be depleted. Rather than continuing to rely on dirty fossil fuels to meet rising electricity demand, several nations are turning to environmentally friendly "renewable" energies. [1]. Among them, wind power and photovoltaic energy signal a faster development in the world and are gradually taking an important place in the electricity market [2]. The competitiveness of wind energy and its increasingly competitive cost with conventional means of production affects the use of this type of energy for the electrification of isolated sites and the connection to the electrical network. In order to improve the electrical power supplying, wind farms made up of several wind turbines are the most suitable solution used by many countries [3]. The majority of these farms are controlled to provide their maximum power with the fault ride through capability [4]. Several recent research works in the field of wind farm are directed towards the design of supervision algorithms with the aim of an optimal power distribution on the various wind turbines. In authors worked on the requirements imposed by the transmission system operator (TSO) for the wind farms integration to the grid without affecting safety and stability. To increase the controllability of the power system, various studies have dealt with the techniques of supervision and control of wind farms such as the control of active and reactive power in the voltage control in and the frequency control The studies detailed in present several autonomous hybrid energy systems based on the kinetic energy of the wind. Energy management and supervision strategies were developed in order to show the interest of integrating storage systems in autonomous applications for improving the quality of the energy produced.

2.0 RELATED WORKS

In an effort to model significant wind farms efficiently and accomplish real-time power optimization, [1] researchers set out to design an ADMM-based distributed power optimisation method taking into account turbine control restrictions. In this paper, we consider the control constraints handling in wind farm power optimization problem, which is of great practical importance but has not been addressed in the literatures. We do so by posing the resulting problem as a constrained nonconvex general form consensus optimization problem. This paper proposes ADMM as a distributed optimization solution for the restricted nonconvex general form consensus optimisation problem, expanding upon the findings in There is a rigorous proof of convergence for the resulting approach [2]. An application example of the suggested method is the power optimization problem in a wind farm subject to control restrictions. The design guarantees that the implemented control action is practical for real turbines, and it is shown that the method can provably identify a stationary point of the wind farm power optimization problem under moderate assumptions. This is not trivial, however, because the power optimization problem is nonconvex. [3]. In the meantime, it allows for turbines to be optimised in fully parallel fashion via turbine-to-turbine message passing across a mesh network and so provides great computation efficiency, scalability and reliability. Many academics have conducted extensive study on the solving algorithm in an effort to increase its efficiency [4]. Calculation of the optimal power flow (OPF) in a decentralized ac system was accomplished with the help of the ADMM. Since it is based on the augmented Lagrange multiplier and the proximal point algorithm, the ADMM does not solve the problems that the first-order approach has. In [5], the distributed interior point technique was used to spread the OPF grid solution and to accomplish simultaneous iterations in all regions. To find the optimal solution for the whole system, the synchronous ADMM was used to the problem of optimizing its many constituent parts in concert. The cascading fault model was built on the basis of studies of vulnerability assessments of crucial nodes in the complex network. [6]. To speed up the calculation of the Nash equilibrium, a stochastic programming (SP)-based energy trading model was developed, which used distributed alternating search algorithms. However, the complexity of the power system network, which is impacted by zonal management and non-sharing of information, makes it difficult to set up a general solution of multi-regional interconnected transmission networks, which is where the aforementioned research optimization algorithms shine [7]. Analytical target cascading (ATC) is a distributed algorithm suitable for solving interconnection and coupling problems. It does not depend on additional information input, can be solved efficiently and accurately only by decoupling variables of the initial problem, and can be used to handle the large-scale renewable energy grid of entropy increase, accelerating the use of centralized ways to work out the majorization of the large-scale optimization process [8]. The application of ATC in scheduling for the next day helps find the best possible solution. The only information carried over from the main problem to the sub-problems during iteration is the border voltage and phase angle [9]. As a result, fewer bytes are transferred throughout each cycle. Due to the existence of interaction variables between the upper and lower layers, ATC first produced a double-deck scheduling solution, and then established a linearized optimization model for active distribution networks [10]. The aforementioned studies serve as useful background reading for this project's OTS implementation

3.0 Wind farm power management strategy

The proposed flowchart for the wind farm energy supervision is illustrated in Fig. In this structure, it was considered that consumers impose a variable demand on the load power. The wind farm power production is directly related to the three wind speed profiles. At first, the total generated power "$P\ G$" is tested and compared to the load power demand "$P\ L$". In the case where "$P\ G$" is less than "$P\ L$", the three turbines T1, T2 and T3 are controlled in MPPT mode in order to deliver their maximum power. Otherwise, each turbine is tested individually. Indeed, if the power generated by a wind turbine "i" is less than the third of the power requested by the loads, this wind turbine is still controlled in the MPPT mode. In the other case, the reference power in which the corresponding wind turbine should be limited is determined.

$$P_{gi\_ref} = \left(P_L - \sum_{j=1}^{n} P_{gj}\right) + P_{gi} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

If the power "$P\ g\ i$" is less than or equal to the reference power "$P\ g\ i\ \_r\ e\ f$", the pitch angle "$\beta\ i\ t$" of the wind turbine "i" receives only the angle "$\beta\ i$" which is proportional to the wind speed. When the wind speed exceeds its nominal wind value, a control of this angle will maintain the mechanical speed as a protection from any possible damage. In the other case, when the power "$P\ g\ i$" is greater than the reference power "$P\ g\ i\ \_r\ e\ f$", the LSU will change the wind turbine operation mode from the MPPT to the LPPT according to the reference power provided from the CSU. For the affected wind turbine, an additional pitch angle "$\Delta\beta\ i$" is instantaneously calculated in order to give an exact tracking of the desired power.

Configuration of the Wind Farm

Fig. 1 shows the configuration of a typical WF with a radial topology. The power generated by WTs is collected by MV feeders and transmitted to the external grid through a HV/MV transformer and HV cables. The buses in the WF include a slack bus at the point of connection (POC), a collector bus and several WT buses.

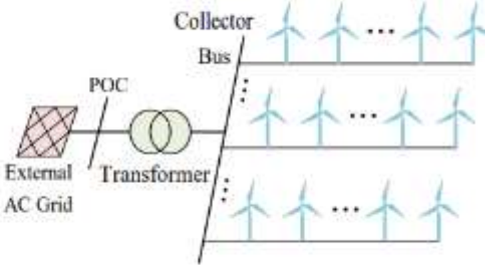

Figure 1. Typical configuration of a WF.

Concept of the ADMM-based DARPC:

The suggested ADMM-based DARPC scheme's control structure is depicted in Fig. The processors inside the WF are divided into the collector bus controller and WT processor. The active and reactive power references of the WF, Pref WF and Qref WF, respectively, are decided by the TSO and delivered to the collector bus controller. In the proposed DARPC scheme, the WF operates in a distributed manner to minimize the power loss inside the WF while regulating the voltage profiles of buses within feasible ranges. Each distributed controller optimizes the active and reactive power references for its corresponding WT to minimize the power flow loss from its parent bus to itself and the voltage deviation of the corresponding bus and maximize the Var capacity of the corresponding WT. Each controller only exchanges information with its neighboring controllers.

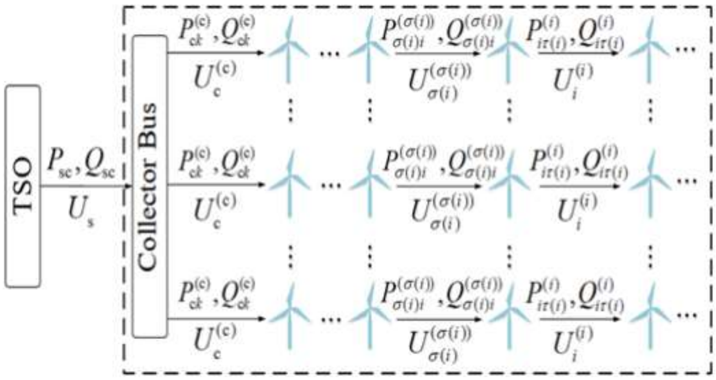

Figure 2. General framework of the proposed ADMM-based DARPC

Wind farm configuration Fig. illustrates a general description of the studied wind farm. This structure is made up of three variable speed wind turbine generators with a total nominal power of 6kW. The control of the wind farm is ensured by two supervision units. The first one is a central supervision unit which instantly manages the wind farm power production according to the load variation and the available power in each wind turbine. The second one is the local supervision unit which receives the information about the reference power from the CSU in order to adapt the production of each wind turbine

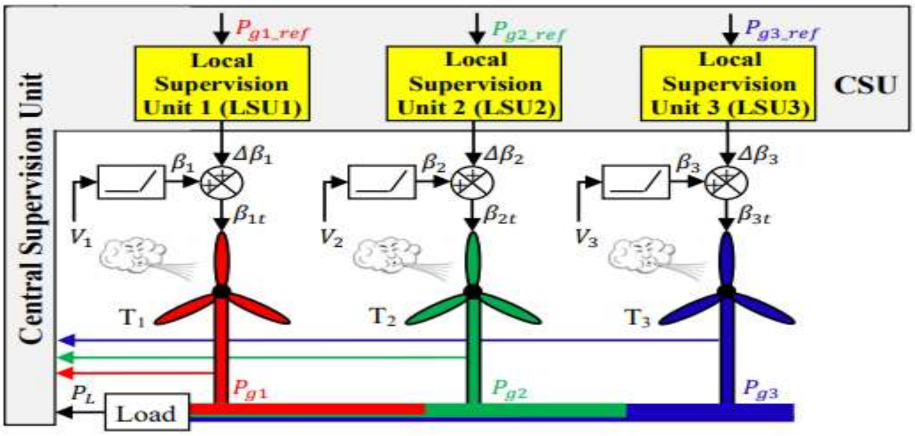

Figure 3: Wind farm structure

4.0 SIMULATION RESULTS

A WF with two feeders, each consisting of 10 × 5 MW WTs, is used to validate the performance of the proposed DARPC method. The power production of the WTs is collected by 33 kV cables with a length of 4 km and sent to the external grid through a 110 kV transmission line. The simulation parameters of the WF are listed in Table I. The control performance of the DARPC scheme is compared with that of the PD-based active and reactive power control scheme. The PD-based control scheme controls the output power of a WT according to its proportion of available power in the total available power, which is easy to complete but is without any optimization control.

The simulated WF was simulated in MATLAB/SIMULINK. The proposed DARPC scheme was implemented in the YALMIP optimization toolbox using MATLAB R2016a and solved by MOSEK 8.1. The total simulation time is set as 500 s. The reactive power dispatch command for the WF is set as -0.1 p.u. and 0.2 p.u

Table 1: Parameters of the WF network transmission line

Parameters	Value
Resistance of the 33 kV Cable, r	0.078 Ω/km
Inductance of the 33 kV Cable, L	0.41 mH/km
Capacitance of the 33 kV Cable, C	0.19 µF/km
Rated Capacity of the Transformer, St	100 MVA
Resistance of the Transformer, rt	0.002 p.u.
Inductance of the Transformer, Lt	0.120 p.u.
Rated Frequency	50 Hz
Penalty constant, ρ	18
Base Current, IB	1749.5 A (rms)

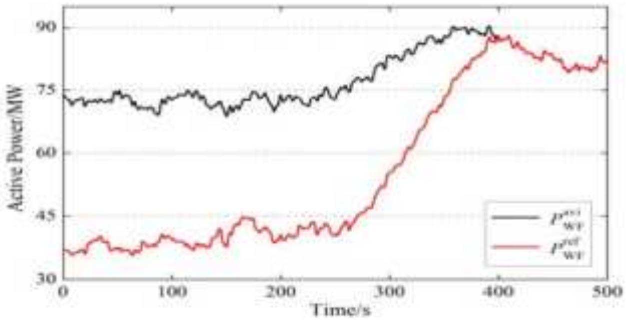

Figure 4: Available active power and active power dispatch command for the WF

The figure shows the available active power and the active power dispatch command for the WF. From 0 s to 250 s, the available active power fluctuates between 65 and 75 MW and increases gradually to 90 MW from 250 s to 400 s. After 400 s, the available wind power decreases to approximately 80 MW. The active power dispatch command for the WF is set to approximately 40 MW from 0 to 280 s and increases with a ramping limit from 280 s to 400 s. At 400 s, the dispatch command reaches the maximum power point. After 400 s, the WF operates in maximum power point tracking (MPPT) mode.

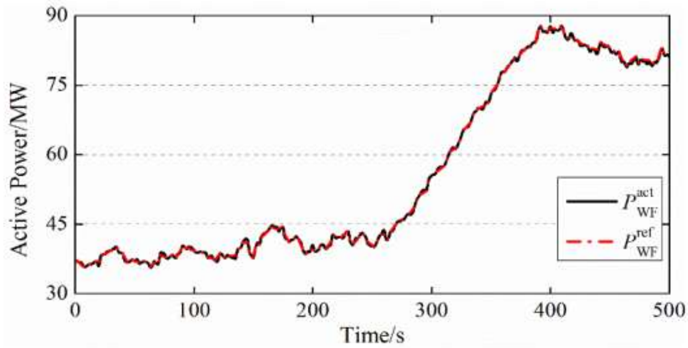

Figure 5: Active power tracking of the WF using the DARPC strategy

The active power tracking performance of the WF with using the DARPC scheme is shown in Fig. The active power output of the WF can track the dispatch command accurately even when the dispatch command fluctuates during the whole simulation period. The PI-based controller in (17.1) can efficiently reduce the error between the dispatch command from the TSO and the actual WF output caused by the linear Dist Flow model.

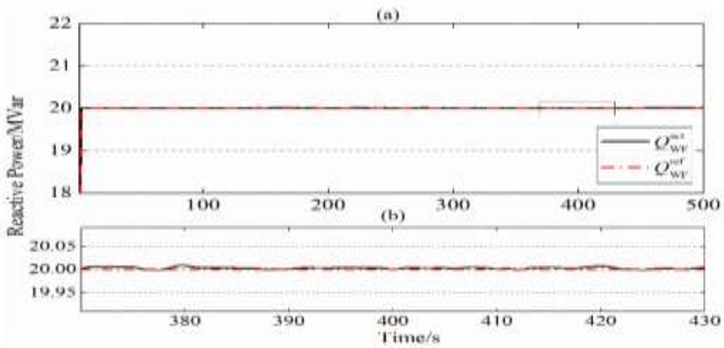

Figure 6: (a) Reactive power tracking of the WF using the DARPC strategy, (b) local magnification.

The convergence performance of the DARPC scheme is shown in Figs. Due to the large amount of data and variables, only the active and reactive power flows of the collector bus and the first four WT buses at the 1st feeder are shown here. The reactive power dispatch command for the WF is set to 0.2 p.u.

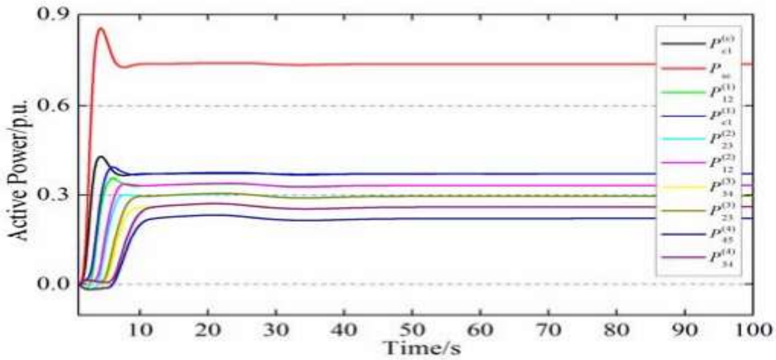

Figure 7: Convergence performance of active power flow.

As shown in Fig. the active power flow calculated in each controller converges to the optimal solution after approximately 40 iterations.

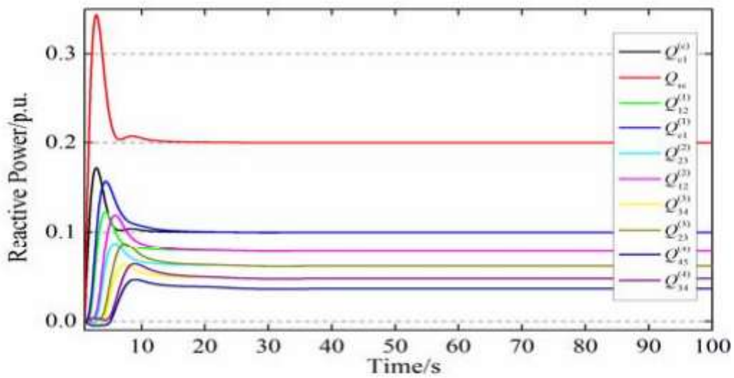

Figure 8: Convergence performance of reactive power flow.

As shown in Fig. the reactive power flow calculated in each controller converges to the optimal solution after approximately 30 iterations. These figures show that the ADMM-based DARPC strategy has fast convergence speed and better steady performance. Considering the communication time, the DARPC strategy can obtain the optimal solution in every control.

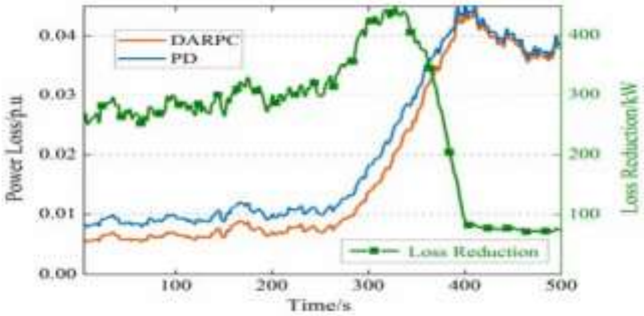

Figure 9: Power loss of the WF with different strategies and the loss reduction when the reactive power reference of the WF is -0.1 p.u.

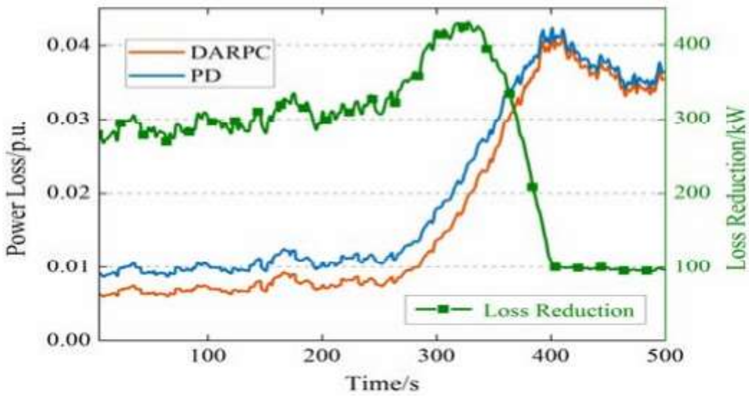

Figure 10: Power loss of the WF with different strategies and the loss reduction when the reactive power reference of the WF is 0.2 p.u.

The simulation results show that the DARPC scheme can efficiently reduce the WF power loss and the voltage deviations of the buses from the rated value while tracking the active and reactive power dispatch commands from the TSO. The DARPC scheme shows more advantages than the conventional PD control scheme.

Conclusion:

In this paper, we present a DARPC system for a WF in order to maximize the Var capacity of each WT while minimizing the network power loss of the WF and the voltage variations of the buses from the specified value. First, a problem of optimization for the WF is stated using OPF. Better operational performance is attained by considering the effects of active power. Second, the ADMM technique is used to break down the optimization issue into smaller, more manageable chunks. To guarantee that the combined active and reactive power output satisfies TSO standards, each controller shares information exclusively with those closest to it. While other distributed/hierarchical control approaches for WFs may optimize active power references, the DARPC scheme optimizes reactive power references as well, all while obeying the TSO's dispatch command. The WF's scalability is enhanced in comparison to traditional centralized optimum control, and the need for a centralized unit is removed.

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