Design of large wind farms using ADMM for real-time control and optimization

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Abstract: In this paper, we propose a distributed optimal reactive power control (DORPC) strategy for reducing generator, converter, filter, and network losses in DFIG-based wind farms (WFs). Total WF losses are reduced thanks to the DORPC's ability to synchronize the reactive power outputs of the DFIG stator and the grid-side converter. By reaching an agreement through ADMM, a decentralized approach to solving the optimal control issue is enabled. Consensus ADMM changes the total WF loss optimization problem into a distributed optimal power flow problem taking into account the best possible performance of DFIGs. Within the WF, the reactive power limit of DFIG-based wind turbines (WTs) and the voltage restriction at all WT terminal buses are taken into account by the optimization problem with local constraints. The DORPC solves the optimal control problem in parallel using the collector bus station controller and WT controllers, sharing information exclusively with nearby nodes. Greater reliability and easy plug-and-play functionality are implied by the lack of a single controller and centralized communication. Twenty DFIG-based WTs were utilized to test the proposed DORPC method in a WF.

Keywords: ADMM. distributed optimal reactive power control (DORPC), DFIGs

1.0 INTRODUCTION

Wind energy is rapidly increasing in popularity and maturity as a renewable energy source (RES). The expansion of wind power generation brings new difficulties due to the intermittent nature of wind power and the interaction between wind farms (WFs) and power networks Due to its excellent controllability and small converter rating, the doubly fed induction generator (DFIG)-based wind turbine (WT) has seen widespread use in contemporary WFs. With power electronic converters, DFIG-based WFs can regulate reactive power independently and offer reactive power assistance for power systems Numerous studies have been prompted by the need to regulate the voltage and reactive power of WFs. To keep the power factor under the POC limit or to supply reactive power support for power systems while following the dispatch command from the TSO the WF is necessary. Static var compensators (SVC) and static synchronous compensators (STATCOM) are examples of dynamic power electronic devices used in WFs for rapid reactive compensation and voltage management Each DFIG-based WT in a WF with DFIGs is wired with a power electronic converter. The reactive power assistance needed by the grid can be provided by the DFIG-based WF using the capabilities of the DFIG-based WTs. Proportional dispatch (PD) is the most popular reactive power control system in WFs because it is straightforward to construct and takes into account the reactive power margin of each DFIG-based WT The WF controller can't get the most out of the WF without the optimum reactive power references for each WT.

To minimize overall active power losses along the cables and the transformers of WTs, particle swarm optimization (PSO) was used for reactive power dispatch in The power loss of the offshore WFs collection system, the grid side converter (GSC) of WTs, and the high-voltage direct current (HVDC) converters were the targets of the optimal control in keep all WF bus voltages within a workable range while minimizing network losses, MPC-based reactive power control approaches were proposed for the massive WF in Total electrical losses of the WF, including losses in cables and WT transformers, as well as losses within wind energy producing systems, were proposed to be minimized by the use of centralized optimal reactive power dispatch algorithms.

2.0 RELATED WORKS

In their study to develop a ADMM-based distributed power optimization method considering turbine control constraints for large wind farms that can be modelled to efficiently achieve real-time power optimization [1]. The control constraints handling in wind farm power optimization problem, that have great practice importance but have not been considered in the literatures, have been considered in this paper by formulating the resulting problem as a constrained nonconvex general form consensus optimization problem A distributed optimization method for constrained nonconvex general form consensus optimization problem is proposed using ADMM, further extending the results in A rigorous convergence proof of the resulting method [2] The proposed method is applied to the wind farm power optimization problem with control constraints as an application example. The design ensures implemented control action feasible for real turbines and it can be shown that the method can provably identify a stationary point of the wind farm power optimization problem under moderate assumptions—note this is nontrivial due to the nonconvex nature of the power optimization problem [3]. Meanwhile, it allows for turbines to be optimized in fully parallel fashion via turbine-to-turbine message passing over a mesh network and thus guarantees high computation efficiency, scalability and reliability. In order to improve the efficiency of solving, many scholars have carried out thorough research around the solving algorithm [4]. In the distributed optimal power flow (OPF) calculation for alternating current systems was achieved by using the alternating direction method of multipliers (ADMM). The ADMM is cannot eliminate the drawbacks of the first-order algorithm because it is based on the augmented Lagrange multiplier and the proximal point algorithm The distributed interior point algorithm was applied in [5] to decentralize the solution of the OPF of the grid and to achieve simultaneous iterations in each region. In the synchronous ADMM was used to solve the coordinated optimization of numerous sub-systems, and then the overall optimization was determined. In based on the research of vulnerability analysis of critical nodes in the complex network, a cascading fault model was established [6]. In an energy trading model based on stochastic programing (SP) was established, and it used distributed alternating search procedures to accelerate the calculation process of the Nash equilibrium. The aforementioned research optimization algorithms can effectively improve the speed of the model solution but do not consider the complexity of the power system network, which is affected by zonal management and non-sharing of information, thus making it hard to set up a general solution of multi-regional interconnected transmission [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]. In ATC is applied to seek the optimal plan for day-ahead scheduling. During iteration, only the voltage and phase angle of the boundary are shared between the main problem and sub-problems [9]. As a result, the amount of data exchanged per iteration is reduced. In a double-deck scheduling solution was established by ATC, and then, a linearized optimization model for active distribution networks is established due to existence of interaction variables between the upper and lower layers. The aforementioned research provides a good reference for this work to conduct OTS [10].

3. Theory of phase angle (PA) control in DVR

Various types of compensation methods for DVR as reported in are effective only during grid side disturbances such as sag/swell, phase jump, fault, etc. and the DVR remains idle during nominal grid conditions. However, in the proposed scheme, the DVR is engaged continuously even at nominal grid voltage, functioning to meet the reactive power demanded by the FSWG. The proposed "Phase Angle" control scheme of DVR in FSWG is explained in this section. The 'PA' control is illustrated with phasor diagram as shown in Fig. The grid voltage Vg is considered as the reference phasor. The terminal voltage Vt is represented to lag the grid voltage Vg by an angle δ whereas the line current is required to be exactly out of phase with grid voltage to maintain unity power factor irrespective of grid voltage variations. Since in general the variation of rotor speed of a FSWG is only about 1–2% of rated speed the FSWG is modelled as a fixed impedance in this work. Therefore, at a given speed, the effective impedance and thereby the real and reactive power of the FSWG can be considered constant if the magnitude of terminal voltage is maintained constant.

δ φ = °− 180 w……………………………….(1)

By maintaining the phase angle δ constant, the unity power factor can be maintained at the grid. Thus the magnitude of the terminal voltage is maintained at the nominal value while the phase of →Vt is also maintained constant at 'δ' with respect to the grid voltage

$$\vec{V_t} = \vec{V_g} + \vec{V_c} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(2)}$$

From (2), the magnitude and phase angle of injected DVR voltage are given by,

$$|V_c| = \sqrt{(V_t cos\delta - V_g)^2 + (V_t sin\delta)^2} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\text{(3)}$$

Distributed solution method based on ADMM

For eliminating the need of a central controller, a distributed optimization framework based on the ADMM is proposed in this subsection. For the collector bus station controller, the optimization problem can be expressed as augmented Lagrangian form,

Optimization problem:

In the DFIG-based WF operation, all DFIG-based WTs inside the WF are assumed to be operated in maximum power point track (MPPT) mode. The active power output of the DFIG at each control period can be considered constant. The WF operator only generates the optimal reactive power references for the DFIG stator and GSC to minimize the total power losses inside the WF. Then, the optimization problem for the centralized optimal reactive power control (ORPC) can be formulated as

$$\min_{Q_s,Q_g} R_s\frac{(Q_s)^2}{V_s^2}+\sum_{j=1}^{|N_f|}\sum_{i=1}^{|N_w|}\left(R_{i-1}^{j}\frac{(Q_{i-1}^{j})^2}{V_s^2}+P_{WT,i}^{Loss,j}\right), \quad \text{(4)}$$

$$-Q_{g,i}^{avi,j}\leqslant Q_{g,i}^{j}\leqslant Q_{g,i}^{avi,j}. \quad \text{(5)}$$

where Q i j s, and Q i j g, are the reactive power provided by the stator and the GSC of the ith DFIG-based WT at the jth feeder, respectively, Q i j s, avi, and Q i j g, avi, are the available reactive power of the stator and the GSC, respectively.

4. SIMULATION RESULTS

A WF with two feeders and 10 × 5 MW DFIG-based WTs connected to each feeder is used for validating the performance of the proposed DORPC method.

Table1: Parameters of the DFIG-Based WF

Parameters	Value	Per Unit Value
Rated Mechanical Power of the WT	5 MW	0.05 p.u.
Rated Stator Phase Voltage	548.48 V (rms)	0.017 p.u.
Rated Stator Frequency	50 Hz	
Rated Rotor Speed	1170 rpm	
Rated Slip	−0.17	
Number of Pole Pairs	3	
Stator Winding Resistance, R_s	1.552 mΩ	0.000142 p.u.
Rotor Winding Resistance, R_r	1.446 mΩ	0.000133 p.u.
Stator Leakage Reactance, X_{ls}	0.400 Ω	0.0367 p.u.
Rotor Leakage Reactance, X_{lr}	0.375 Ω	0.0323 p.u.
Magnetizing Reactance, X_m	1.733 Ω	0.1591 p.u.

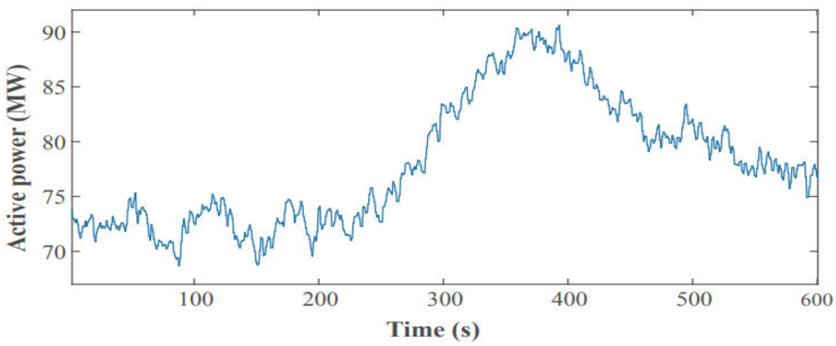

Figure 1: Total available wind power for WF.

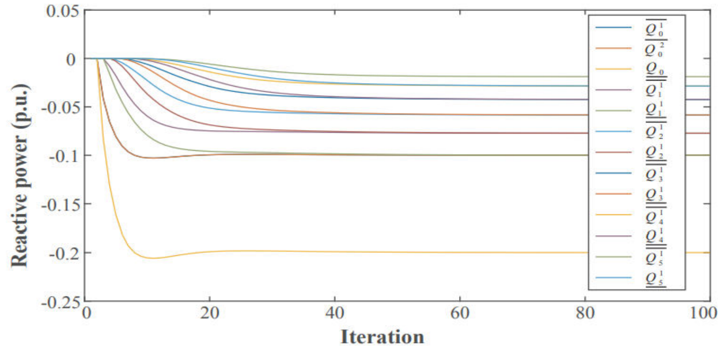

Figure 2: Convergence performance with reactive power reference of WF set to 0.2 p.u.

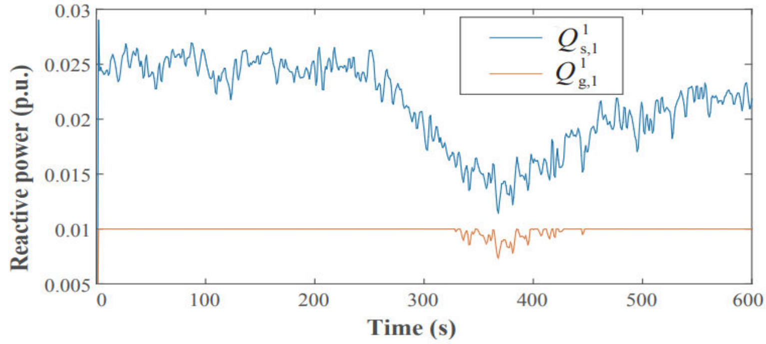

Figure 3: Reactive power dispatch inside 1st DFIG-based WT at 1st feeder with WF reactive power reference set to 0.2 p.u.

The convergence performance of the DORPC scheme when the reactive power reference of the WF is set to 0.2 p.u. is shown in Fig. Given the excessive amount of data, only the convergence performance of the local variables of the collector bus station and the first five WT

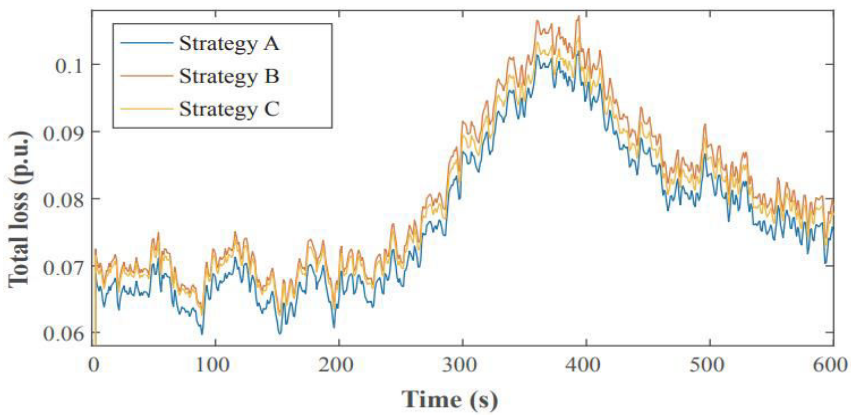

Figure 4: Total losses of WF controlled by different strategies when reactive power reference of WF is 0.1 p.u.

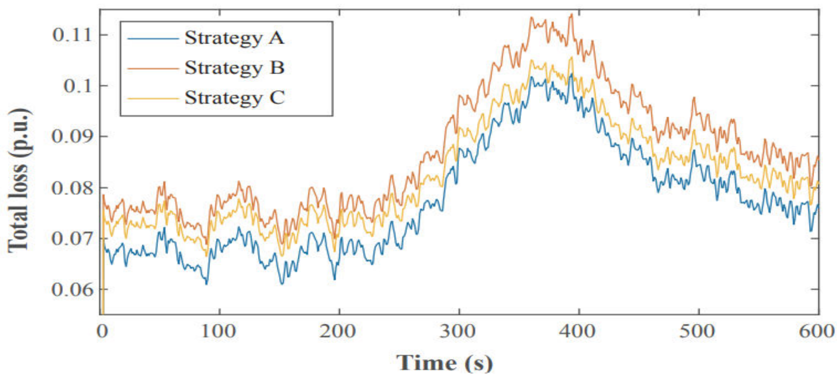

Figure 5: Total losses of WF controlled by different strategies when reactive power reference of WF is 0.2 p.u.

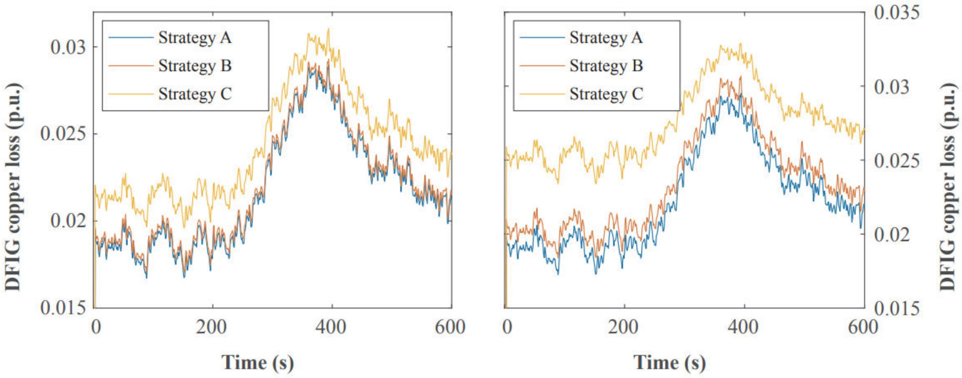

Figure 6: Copper loss of DFIG-based WTs, with QWF ref = 0.1 p.u. (left) and QWF ref = 0.2 p.u. (right).

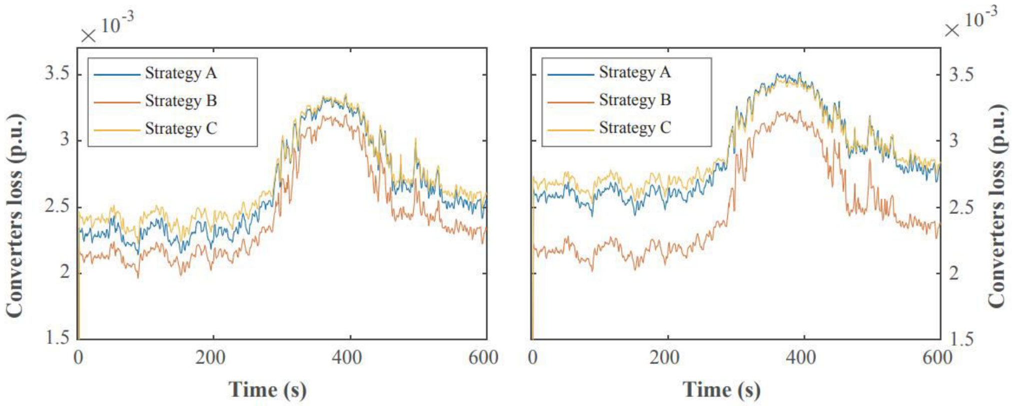

Figure 7: Converters loss in DFIG-based WTs, with QWF ref = 0.1 p.u. to the left, QWF ref = 0.2 p.u. to the right.

Table 2: Losses of different parts in the WF with different control strategies

Different simulation time points	Power losses in the WTs (p.u.)			Network losses (p.u.)			Total power losses (p.u.)		
	A	B	C	A	B	C	A	B	C
Average power loss	0.0248	0.0254	0.0300	0.0529	0.0618	0.0525	0.0777	0.0872	0.0825
Power loss at 100 s	0.0215	0.0221	0.0275	0.0458	0.0537	0.0453	0.0673	0.0758	0.0728
Power loss at 250 s	0.0216	0.0223	0.0276	0.0463	0.0542	0.0458	0.0679	0.0765	0.0734
Power loss at 320 s	0.0278	0.0285	0.0321	0.0594	0.0692	0.0591	0.0872	0.0977	0.0912
Power loss at 380 s	0.0317	0.0324	0.0351	0.0677	0.0787	0.0677	0.0994	0.1110	0.1028
Power loss at 500 s	0.0268	0.0275	0.0315	0.0575	0.0670	0.0571	0.0844	0.0945	0.0886

the reactive power output of the 1st WT at the 1st feeder when the reactive power reference of the WF is set as 0.2 p.u. Qs and Qg begin to fluctuate simultaneously at 300–400 s given the buses are shown here. Simulation results reveal that the local variables converge to a common value after 40 iterations, implying good convergence performance. It takes about 4–7 ms to complete an iteration. As a result, the time required to complete an optimization is less than

5.Conclusion:

In this work describes a DORPC approach to minimize losses in DFIG-based WF. By coordinating the DFIG stator and the GSC reactive power output optimally, we solve the optimal control problem posed by the OPF model. Reactive power limits of WTs and a workable voltage range are taken into account in the optimization problem. The consensus ADMM achieves a decentralized solution to the optimal control issue. To determine the best possible values for their local variables, all controllers simultaneously compute using only information gleaned from their neighbors. Case studies show that the DORPC approach effectively cuts overall WF losses while obeying the TSO's reactive power dispatch instructions.

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